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COMPARATIVE EVALUATIONS OF THE RADC/HSU TEXTURE MEASUREMENT SYSTEM WITH PERCEPTUAL ANALYSES

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Earlier it was determined that the essential information for terrain discrimination was contained in three tone-texture variables: mean density, first and second neighbor contrasts. In this study, this fundamental concept was successfully sustained using a Monte Carlo technique.

To determine the relationships between the RADC/Hsu texture measurement system and human perceptual judgments, four population maps with 20 subjects

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cont and four terrain types with 40 subjects were analyzed. The first analysis (20 subjects) yielded a clear-cut tone and texture ~~(d-)~~ "perception model" with a multi-dimensional scaling technique. The second analysis (40 subjects), according to a minimum stress criterion (free-running), yielded a less-interpretable tone and "texture plus structure" perception model.

A fixed model using computed tone and texture parameters, however, gave a more satisfactory and interpretable result. Accordingly, 50% ~~percent~~ of the subjects indicate a near-perfect fit, another 25% ~~percent~~ have a moderate fit and the rest (25% ~~percent~~) belong to lack-of-fit and no-fit categories.

The man-machine interaction pattern in these models reveal that the machine classifier weighted the tone parameter heavier than the texture parameter by a factor of 1.5, whereas the human subjects displayed interesting individual differences as to how they weighted these two dimensions.

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Dr. Shin-yi Hsu
Dr. Richard Burright

Comparative Evaluations of the RADC/Hsu Texture Measurement System With Perceptual Analyses

A. INTRODUCTION

In a broad methodological framework, pattern recognition may be conceived of as using two highly integrated processes; namely, feature extraction and classification. Such processes may be performed "manually" by the human observer, and/or by automated operations. In the area of image data processing, automated methods have become increasingly important since they are potentially capable of more efficient mass data processing. On the other hand, the error-rate of current automated methods is still high when compared to human photo-interpretation (on a more limited scale). Thus, efforts have been made in the pattern recognition sciences to utilize human perceptual attributes (abilities) in designing feature extractors and classifiers; e.g., Hsu's texture measure (1977), and Mitchell's max-min feature descriptor (1977).

Under the sponsorship of USAF/Rome Air Development Center (RADC), and based upon his earlier study of visual versus statistical discrimination of maps, Hsu used a multivariate normal model to develop a highly accurate texture measure with 17-23 feature variables for automatic recognition of terrain types (Hsu, 1975, 1977). According to a stepwise discriminant analysis, almost all of these feature variables contribute significantly to the discrimination power of the Mahalanobis classifier. But not surprisingly, extracting about 20 feature variables makes processing time enormous; for instance, it takes 90 minutes CPU time to process a 256 x 256 pixel with FORTRAN programming language. Therefore, there is a definite need to drastically reduce processing time while maintaining the high level of accuracy in the decision map.

In Phase II of the USAF/RADC project noted above, an effort has been made to design a new classifier based on the stable distribution model instead of the normal distribution model: thus, e.g., skewness parameters of the spectral/texture data are incorporated into the classifier. In contrast to the 2-parameter (mean & variance) normal model, the stable distribution model uses four basic parameters--location (comparable to mean), scale (comparable to variance), stable index, and symmetry parameter. In theory, this new classifier should have more discrimination power than the one based on the normal model. Furthermore, the increase in the classifier parameters could require fewer variables in the feature extractor component of the pattern recognition system, and thus reduce processing time. Indeed, preliminary experiments (based on five frames) have indicated that only three texture variables (and certainly no more than five) are required in the new classifier to achieve the same performance obtained with the old (normal model) classifier which required 17-23 texture variables! The three variables thus far implicated primarily are: average grey-level, first neighbor contrast, and second neighbor contrast. Processing time is therefore reduced to only 15-20 minutes CPU time (FORTRAN programming) for processing the same 256 x 256 pixels. Thus, with appropriate programming procedures, the new system could potentially provide the machine base for a real-time interactive pattern recognition system.

Currently, Whitman Richards (of MIT) has been conducting texture perception studies for the Air Force under the sponsorship of the Advanced Research Projects Agency (cf., Richards, 1977). Richards has concluded that most uniform textures can be simulated by three or four variables, provided that these variables contain the basic elemental tokens of the graphic display. His approach to texture perception has employed a "generalized colorimetry" technique analogous to that used so successfully in studying human color vision. The ability to create texture metamers for humans by using 3-4 variables clearly suggests that a considerable saving in communicating critical texture information can be achieved.

However, Richards' work has been based on the generation of random (or quasi-random) dot patterns. Specifically, his results are derived by visually matching a pattern of spatially distributed random dots created by three grey-levels with one created by 63 grey levels. Such texture metamers can also be achieved with three grating "primaries." In addition, using n-gram statistics to provide statistical control of any adjacent point in a random-dot texture pattern, Purks and Richards (1977) have shown that constraints imposed on span lengths less than three--regulating grey levels and spatial frequency content--have the most significant influences on texture discrimination. Note that the modified Hsu/RADC machine system can successfully employ texture variables defined by average grey-level, first neighbor and second neighbor contrasts.

The work cited above, coupled with the prior and continuing efforts of others (notably, cf: Campbell, 1974; Ginsberg, 1973; and Pollen and Tyler, 1974) concerning psychological, psychophysical, physiological, and neurological techniques, strongly suggest that the human visual perceptual system employs 3-4 "filters/channels" in analyzing texture. However, this filtering process, as measured in the simulated, random-dot environment, involves variables directly concerned with degree of resolution rather than directly specifying potentially more substantive informational measures contained in texture patterns of two or more dissimilar real-world scenes, such as vegetation vs. soil, etc. In machine image data processing systems, resolution processes *per se* are a function of optical scanning and digitization/generalization techniques.

On the other hand, our work to date provides empirical evidence that a 3-4 texture variable discrimination system can be implemented to solve the real-world texture discrimination problem in an image data processing environment using a feature extractor coupled with a classifier based on non-linear discriminant functions. In this context, such a machine system will enable us to quantitatively characterize and simultaneously manipulate the real-world data which it employs; this important fact will also enable us to directly and quantitatively compare the machine system's performance with that of the human visual system and should provide new insights regarding texture/pattern perception of real-world images by both man and machine. Thus, our major thrust in this regard will be to quantitatively characterize real-world image information employed, and assess and compare the effects of changes in that information on the pattern classifications produced by both the machine system and human observers.

From the brief review just provided, it certainly appears that important convergences are emerging from the study of human visual perception and machine-oriented image processing methods. The goal of this study is to investigate further the relationship between these two information processing/discrimination systems by means of a comparative analysis of the RADC/Hsu texture measure/classifier using computer simulations and human perceptual tests. It is expected that the basis for a truly effective real-time, man-machine interactive processing system could be derived from such investigations.

B. COMPUTER SIMULATIONS OF TEXTURE PATTERNS WITH SELECTED VARIABLES

The goal of the following experiments is to determine how well the total texture-tone information of terrain patterns can be represented by the "essential variables" described earlier from a generation of two dimensional patterns with Monte Carlo techniques. The measurement for the distance between two spatial patterns is the Mahalanobis D^2 derived from a multivariate discriminant analysis. Here D^2 approaching zero means the two spatial patterns are essentially the same. The "threshold point" (D^2) determining if two patterns are statistically different can also be obtained since the sampling distribution of D^2 distances is essentially a χ^2-distribution.

For performing the following experiments, we have selected four terrain patterns from the RADC/GALA frame: Vegetation, Cultivated Field, Pavement and Edge Pavement. Each pattern is composed of (15 x 15) picture elements (or pixels).

(1) Experiment 1: Uniform Patterns

Experiment 1 employed the following variables to generate two dimensional spatial patterns:

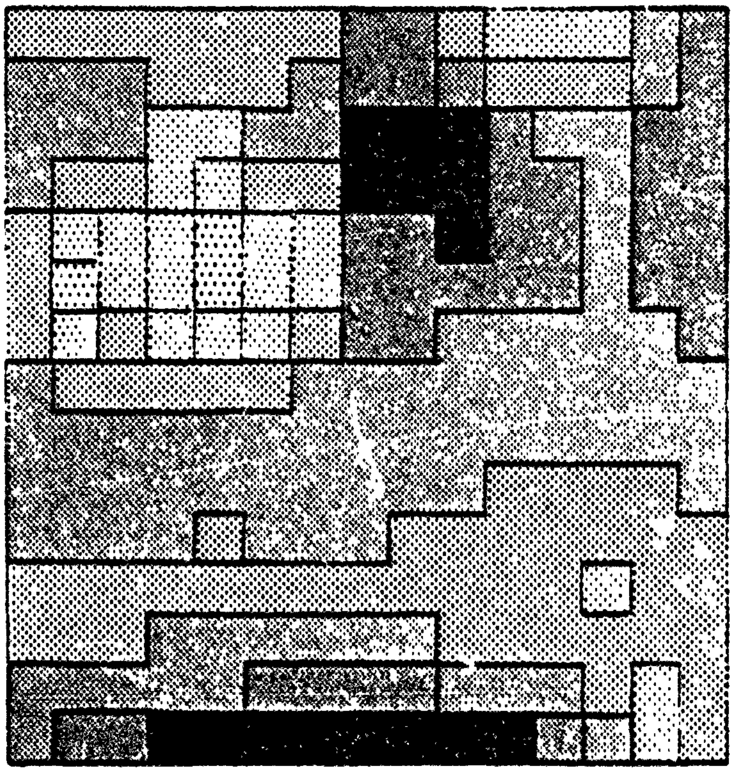
Means	Standard Deviations
Mean Density	Standard Deviation of Density
1st Neighbor Contrast	Standard Deviation of 1st Neighbor
2nd Neighbor Contrast	

It is clear here, we would like to control the distribution of tone (density) and 1st neighbor contrast (texture) first, and let 2nd neighbor contrast be controlled only by the mean. The following figure gives a comparison between the original and the computer simulated patterns from experiment 1.

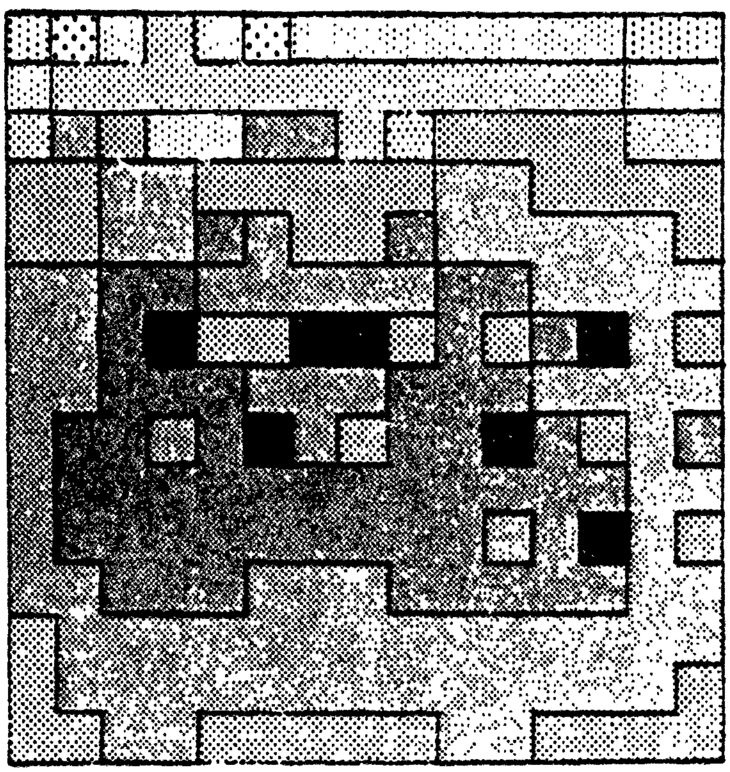
To assess the degree of similarity (or dissimilarity) between the original pattern and the simulated patterns, discriminant analyses were performed to determine the D^2 distance among these patterns. Table 1 gives the results.

FIGURE 1: Texture Patterns of Edge Pave

A. Original Image



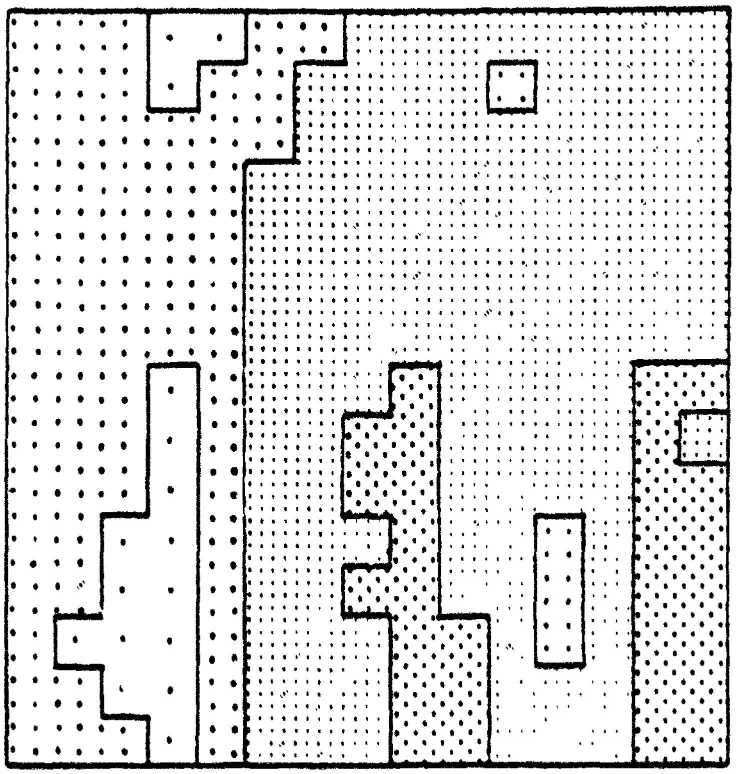
B. Computer-Simulated Pattern (Gen Pic)



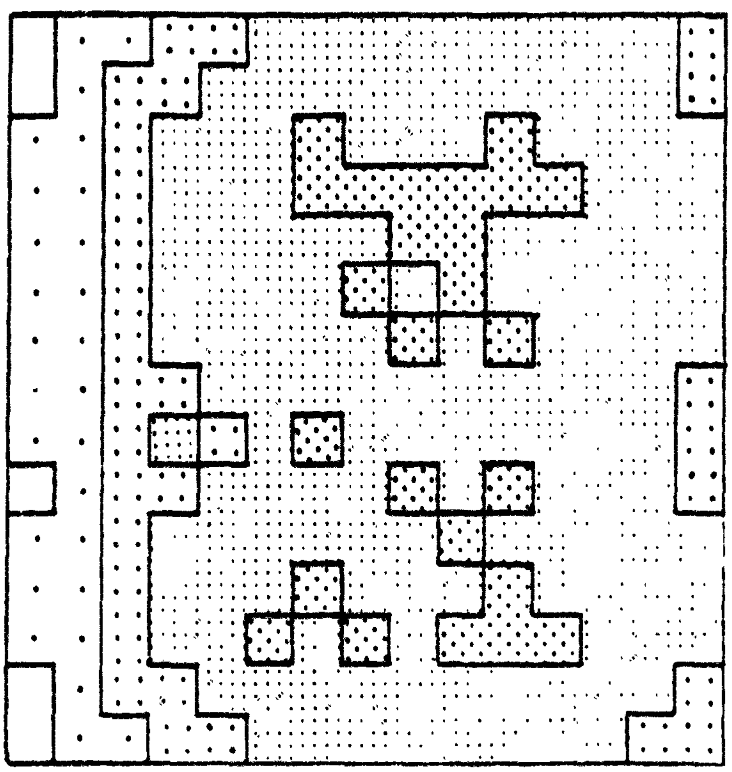
The Mahalanobis D^2 Between A and B is 0.6

FIGURE 2: Texture Patterns of Pave

A. Original Image



B. A Computer Simulated Pattern (Gen Pic)



The Mahalanobis D^2 Between A and B is 0.1

TABLE 1. D^2-Distances Among Textural Patterns From Image and Simulations

D^2		Image				Simulation			
		I VEGN	CFLD	PAVE	EDPV	II VEGN	CFLD	PAVE	EDPV
IMAGE	VEGN	0	47.2	1043.4	235.0	0.1	45.9	1005.2	203.6
	CFLD	603.4	0	8661.9	1209.6	666.8	0.1	8268.1	1041.5
	PAVE	327.1	202.3	0	106.7	334.3	203.8	0.1	126.6
	EDPV	45.7	15.4	58.3	0	47.8	15.7	54.4	0.8
SIMULATION	VEGN	III 0.4	185.8	3115.6	532.2	IV 0	181.3	3001.3	488.7
	CFLD	592.5	0.1	8843.6	1114.2	656.0	0	8442.3	930.2
	PAVE	1265.5	726.7	0.5	476.5	1293.7	732.6	0	535.0
	EDPV	43.9	12.3	77.0	0.3	46.1	12.5	72.2	0

QUAD. I — Image against image

II — Image against simulation

III — Simulation against image

IV — Simulation against simulation

While Quad. I of Table 1 gives D^2 distances among four terrain patterns from the image, Quad. IV indicates the same statistics for simulated patterns. Thus, the comparison between image and simulation can be obtained D^2's in Quad. II and III, specifically the figures in the principal diagonals. The figures in Quads. II and III are not identical (or symmetric) because separate dispersion matrices of each training set instead of a pooled dispersion matrix for all training sets were used in the computation of D^2 from the following equation:

$$D^2 = (Y - \mu_i)' \, Q_i^{-1} \, (Y - \mu_i)$$

Y is observed texture pattern

μ is centroid of a training set

Q_i is the dispersion matrix related to μ

-1 stands for inverse of a matrix

$'$ stands for transpose of a matrix

This also explains the fact that D^2 computed from A to B is different from D^2 computed from B to A since the dispersion matrix of A is different from that of B.

The results indicate that the simulated patterns are essentially the same as the original image patterns in this machine comparison, since none of the D^2-distance exceed 1.0.

To verify the above conclusion, we have also computed the stable parameters of both image and simulated patterns to determine the distributional characteristics of the patterns (Table 2). The results indicate that the distributional characteristics between image and computer simulated patterns are essentially the same.

TABLE 2. Stable Parameters of Image vs Simulated Patterns
(Experiment 1)

		A		B		C		D	
		VEGN		CFLD		PAVE		EDPV	
		Image	Simulation	Image	Simulation	Image	Simulation	Image	Simulation
Variable 1:	Mean Density								
Stable	Location	8.6287	11.57	41.9111	42.4677	166.5664	177.1202	85.7286	103.3787
Parameters:	Scale	4.3599	2.0414	0.9051	0.5158	7.2572	3,1689	7.3936	4.6023
	Alpha	1.600	1.200	1.700	1.2000	1.600	1.1000	1.6000	1.1000
	Beta	-1.00	1.000	-1.000	1.000	1.000	1.0000	0.3000	1.000
Variable 2:	1st Neighbor Contrast								
Stable Parameters:	Location	2.4443	2.4936	1.9465	1.9456	3.4904	3.4729	8.1969	7.4334
	Scale	0.6477	0.6398	0.3973	1.0299	0.6435	0.8223	2.6758	3.1403
	Alpha	1.900	1.9900	1.9900	1.9000	1.7000	1.7000	1.4000	1.9000
	Beta	-1.000	-1.000	0.1000	1.000	0.8000	0.7000	1.000	1.000
Variable 3:	2nd Neighbor Contrast								
Stable Parameters:	Location	3.6711	3.7152	2.1293	2.8633	5.3006	5.7325	12.5077	11.4775
	Scale	1.3365	1.5030	0.5197	0.9356	1.9979	2.3614	5.2985	4.5839
	Alpha	1.700	1.7000	1.8000	1.3000	1.9000	1.6000	1.5000	1.6000
	Beta	1.000	0.9000	1.000	1.000	1.000	0.9000	1.000	1.000

(2) Experiment 2: Non-uniform Patterns

To create more texture information in a given pattern, we intentionally used a mixture of two terrain types to create a spatial pattern. Four such patterns are:

(1) Soil + Pave

(2) Pave + Edgepave

(3) Vegetation + Cultivated Field

(4) Cultivated Field + 2nd Pave

We have also tried to simulate those patterns using the computer simulation techniques described in Experiment 1. However, due to sharp, sudden tonal differences at the edge zones between two terrain types, the simulated patterns failed to converge, and therefore, "similar" simulation patterns cannot be obtained.

(3) Experiment 3: Simulation by the use of Mean Density, Skewness and 2nd Neighbor Contrast

We mentioned earlier that skewness ranked high as a possible discriminator of terrain type. Thus, in Experiment 3, we tried to see whether spatial patterns can be simulated successfully using skewness in conjunction with other variables. Specifically, these variables used for Experiment 3 are:

Mean Density

1st Neighbor Contrast

2nd Neighbor Contrast

Skewness

Standard Deviation

Thus compared to Experiment 1, we replaced "standard deviation" of the 2nd neighbor contrast with skewness in Experiment 3. The results are given in Table 3. From Table 3, we can immediately notice that the locations (means) of

TABLE 3. Stable Parameters of Image vs Simulated Patterns
(Experiment 3)

		A		B		C		D	
		VEGN		CFLD		PAVE		EDPV	
		Image	Simulation	Image	Simulation	Image	Simulation	Image	Simulation
Variable 1:	Mean Density								
Stable	Location	8.6287	9.9017	41.9111	41.9710	166.5664	164.8379	85.7286	85.0229
Parameters:	Scale	4.3599	0.7713	0.9051	0.9208	7.2572	0.0654	7.3936	1.7224
	Alpha	1.600	1.7000	1.700	1.8000	1.600	1.0100	1.6000	1.7000
	Beta	-1.00	1.0000	-1.000	0.6000	1.000	0.0	0.3000	0.7000
Variable 2:	1st Neighbor								
Stable	Contrast								
Parameters:	Location	2.4443	3.0112	1.9465	1.9008	3.4904	5.0384	8.1969	9.6938
	Scale	0.6477	1.7851	0.3973	0.6018	0.6435	4.3474	2.6758	8.0555
	Alpha	1.900	1.8000	1.9900	1.8000	1.7000	1.9000	1.4000	1.9000
	Beta	-1.000	0.7000	0.1000	0.5000	0.8000	1.0000	1.000	1.0000
Variable 3:	2nd Neighbor								
Stable	Contrast								
Parameters:	Location	3.6711	6.2446	2.1293	2.1070	5.3006	127.0693	12.5077	241.9623
	Scale	1.3365	1.4672	0.5197	1.0173	1.9979	1.9771	5.2985	3.7567
	Alpha	1.700	1.2000	1.8000	1.7000	1.9000	1.0100	1.5000	1.0100
	Beta	1.000	1.0000	1.000	0.7000	1.000	1.0000	1.000	1.0000

2nd neighbor contrast in PAVE and EDPV are completely difference between the original image and simulated patterns. By examining the simulation processes, we discovered that many variables are significantly affected by skewness; therefore, it is very difficult to control this many variables simultaneously.

(4) Experiment 4: Computer Simulation With Variables: Mean Density, Standard Deviation and Mean Deviation

Experiment 4 was intended to test whether a given pattern can be simulated successfully using "deviation from mean" parameters in conjunction with mean density. The results are given in Table 4.

From the above four experiments, we can conclude that:

1) The result from Experiment 1 with 5 variables (mean density, 1st neighbor contrast, 2nd neighbor contrast, standard deviations of density and 1st neighbor contrast) yielded the best result.

2) Skewness parameter is very difficult to control in computer simulations.

3) Standard deviation seems to be a useful parameter in describing spatial patterns, as indicated from Experiment 4.

We also asked 40 human observers (see Section D, Experiments 5 and 6 below) to place the simulated patterns derived from Experiment 1 (above) with their "nearest neighbors" among the actual image representations of Cultivated

Field, Vegetation, Edgepave, and Pavement, and then judge the difference between these selected nearest neighbor pairs. Thirty-nine of the 40 subjects placed the machine appropriate simulations with .heir image counterparts--the one subject who "erred", placed the Edgepave simulation with the Pavement image, and vice versa. Of course, all subjects agreed that differences among these "nearest neighbor" pairs were still apparent, since the simulation technique allowed random placement of "pixels" within the 15 x 15 patterns. Considerable individual differences were apparent in the subjects' judgments of how different (on a 0-10 scale) these "nearest neighbors" were. The dimensions involved here is undoubtedly one that might be called "structure" (as opposed to "tone" and "texture"), and will be considered later in Sections D and E.

TABLE 4. Stable Parameters of Image vs Simulated Patterns
(Experiment 4)

		A		B		C		D	
		VEGN		CFLD		PAVE		EDPV	
		Image	Simulation	Image	Simulation	Image	Simulation	Image	Simulation
Variable 1: Stable Parameters:	Mean Density								
	Location	8.6287	9.8573	41.9111	42.0035	166.5664	165.1972	85.7286	85.5846
	Scale	4.3599	0.4993	0.9051	0.1828	7.2572	0.8241	7.3936	1.2580
	Alpha	1.600	1.9900	1.700	1.9900	1.600	1.9900	1.6000	1.9900
	Beta	-1.00	0.1000	-1.000	0.1000	1.000	0.1000	0.3000	0.1000
Variable 2: Stable Parameters:	1st Neighbor Contrast								
	Location	2.4443	6.5008	1.9465	2.3805	3.4904	10.7308	8.1969	16.3795
	Scale	0.6477	5.0582	0.3973	1.8522	0.6435	8.3495	2.6758	12.7446
	Alpha	1.900	1.5000	1.9900	1.5000	1.7000	1.5000	1.4000	1.5000
	Beta	-1.000	0.9000	0.1000	0.9000	0.8000	0.9000	1.000	0.9000
Variable 3: Stable Parameters:	2nd Neighbor Contrast								
	Location	3.6711	2.6258	2.1293	0.9615	5.3006	4.3342	12.5077	6.6158
	Scale	1.3365	2.2468	0.5197	0.8227	1.9979	3.7086	5.2985	5.6609
	Alpha	1.700	1.9900	1.8000	1.9900	1.9000	1.9900	1.5000	1.9900
	Beta	1.000	0.1000	1.000	0.1000	1.000	0.1000	1.000	0.1000

C. TEXTURE PERCEPTION OF CHOROPLETH MAPS

The perception of visual texture, though poorly understood, has long been recognized by aerial photo-interpreters and psychologists as an important characteristic for the identification of objects and scenes (Avery, 1968; Gibson, 1950; Koffka, 1935; Reed, 1973). Recently, computer scientists, electrical engineers, geographers and other scientists have vigorously engaged in physical/mathematical texture analyses of images. However, as shown in the literature reviewed by Rosenfeld (1975), Haralick (1975), Landgrebe (1978) and Hsu (1978), the bulk of the studies have centered on the development of texture measurements for mathematical discrimination of patterns. Few studies have attempted to relate these digitized image measurements to the visual texture recognition process (Mitchell, et al, 1977; Tamura, Mori and Yamawaki, 1978; Hsu, 1978; Hsu and Burright, 1979), although efforts have been made regarding texture perception by humans (Lipkin and Rosenfeld, 1970; Pickett, 1970; Ginsburg, 1973; Pollen and Taylor, 1974; Pribrum, 1974; Rosenfeld, 1975; Richards, 1978).

Using "random-dot" patterns, and a matching procedure analogous to that employed in human colorimetry, Richards (1978) has recently shown that visually equivalent textures (metamers) can be achieved by appropriate manipulations of a set of 3-5 "primaries." For instance, he has shown that the texture of a random-dot pattern with 63 greytone levels is not perceptually different from that of a pattern consisting of only three greytone levels. Obviously, the human visual system involves certain filtering processes. However, the generalizability of Richards' results to real-world pattern recognition and of machine texture analyses to human perception is poorly understood. This section presents some of our initial attempts to address such questions more directly. Specifically, we have compared human similarity/difference judgments of textural patterns based on real-world images with machine texture measurement outcomes developed using local statistics from moving (3 x 3) and (5 x 5) pixel windows as employed in the RADC/Hsu texture analysis (Hsu, 1978). Such comparisons include the use of non-metric,multi-dimensional scaling techniques (Takane, Young, and de Leeuw, 1977), which enable us to construct models for human and machine processes using microtexturally common and specifiable image conditions.

A Short Review of "Perceptually-based" Texture Feature Extractors

Among the texture measures developed for image processing by machine, a few have been termed "perceptually-based"--but, for obvious reasons, such terminology certainly should be considered debatable at present. This section reviews briefly Mitchell/Myers/Boyne's Max-min Descriptor (1977), Tamura/Mori/Yamawaki's texture feature extractor (1978), and the RADC/Hsu texture measurement system (1978).

Based on Mitchell's earlier work (1976), Mitchell/Myers/Boyne published their Max-min Descriptor in 1977. Their texture parameters were obtained from the number of peaks (Max) and troughs (Min) along a scan line using several thresholds; e.g., given three threshold settings, three parameters based on the sum of peaks and troughs provided three texture measurements. This texture descriptor has been considered perceptually-based because it was inferred from the psychophysical literature that the human visual system tends to respond to local extremes. This texture feature extractor also has been tested against Haralick's grey-tone co-occurrence method (1973), and shown to be equally effective for machine discrimination of patterns; however, the Max-min Descriptor is computationally much simpler.

Unlike Mitchell/Myers/Boyne's intuitive approach, Tamura/Mori/Yamawaki (1978) attempted to develop a set of complicated texture measurements from a relatively large group of pixels (128 x 128) which were supposedly visually identifiable texture features such as: coarseness, contrast, directionality, line-likeness, regularity and roughness--a macro-texture approach. Human experiments also were conducted with often used textural patterns produced in Brodatz' (1977) photographic album of textures. The authors indicated that their perceptually-based texture feature extractor did not perform well in similarity judgment tasks.

To investigate the relationship between the human performance and a machine solution regarding similarity judgments of texture patterns as revealed in choropleth maps, Hsu (1974) devised a 10-variable texture measure coupled with a normal model classifier to analyze differences (in terms of Mahalanobis D^2) among map surfaces. These variables were extracted from the wave-form parameters of both x and y axis scan lines, and involved: (1) area above datum, 2) area below datum, 3) sum of the peak positions from origin, 4) sum of contrast values from peaks to troughs, and 5) sum of the number of peaks and troughs. Since a very high coefficient of correlation ($r = 0.97$)existed between the distances judged by human subjects and the machine solution (D^2), this ten variable system was viewed as perceptually-based.

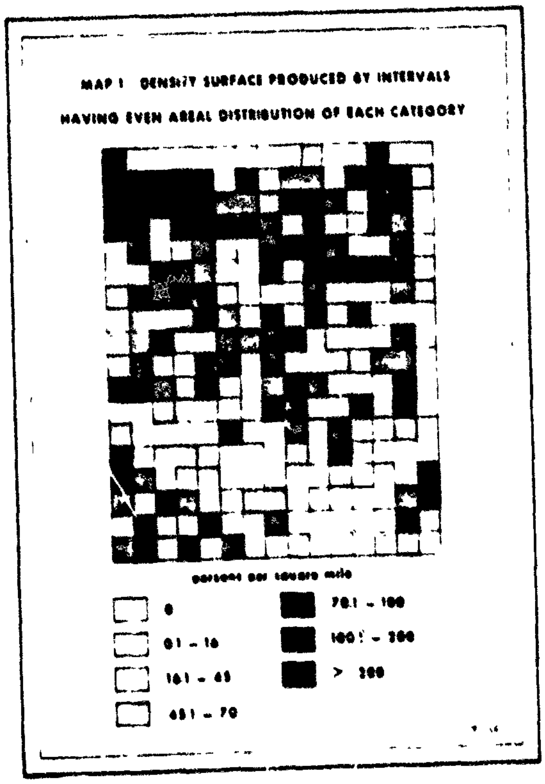
The RADC/Hsu Texture Feature Extractor/Classifier System

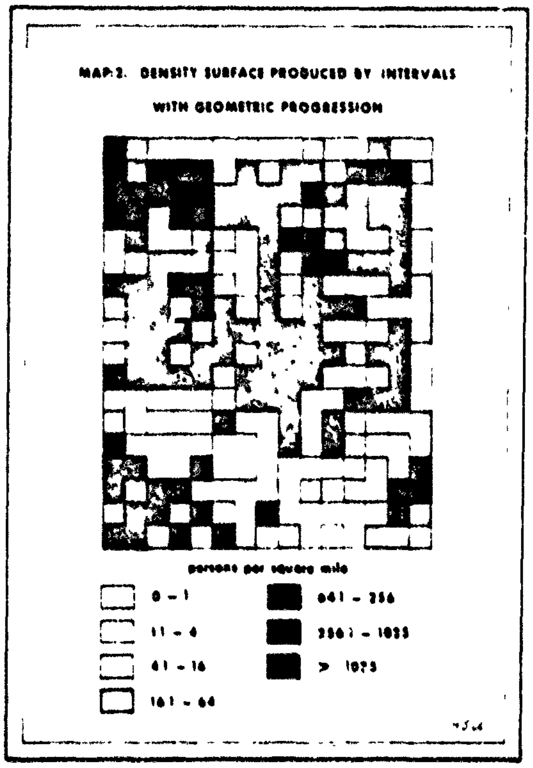
As reported in 1978, Hsu (under the sponsorship of U.S. Air Force/Rome Air Development Center) developed a new texture measure with 17 and 23 variables derived from a (3 x 3) and a (5 x 5) moving grid, respectively. The original (Hsu, 1974) five wave-form parameters were included in this system. This texture feature extractor has been shown to be highly effective; e.g., in reference to ground-truth information, a hit-rate of 85-90% has been obtained regarding land-use analysis from digitized, panchromatic images (Hsu, 1977).

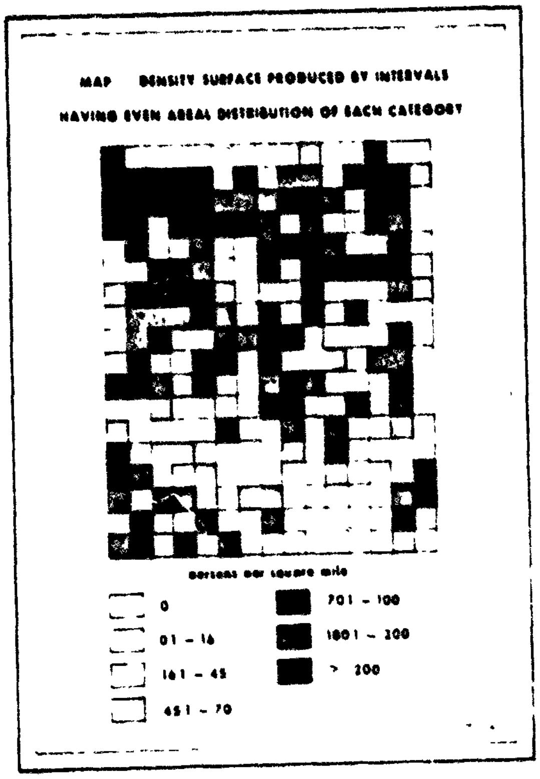
The major difference between the 10-variable wave-form system (Hsu, 1974) and the 17-23 variable system (Hsu, 1978) is that the former was based on a concept of macro-texture analysis, whereas the latter is derived from a micro-texture apprcach. That is, the latter system uses a moving grid (3 x 3 or 5 x 5 pixels) where the center-point is treated as the control point representing characteristics of the relatively small control (grid) area. With this control point/control area concept we are able to generate a vector of texture variables for a single pixel, thus allowing us to perform a pixel-by-pixel classification task with black and white image data. Indeed, we believe that machine similarity measurements, especially if they are expected to relate generally to human perception, should be made on micro-textural features instead of visually apparent macro-textural features which already have been subjected to largely unknown and labile integrative processes (cf., Kolers, 1972).

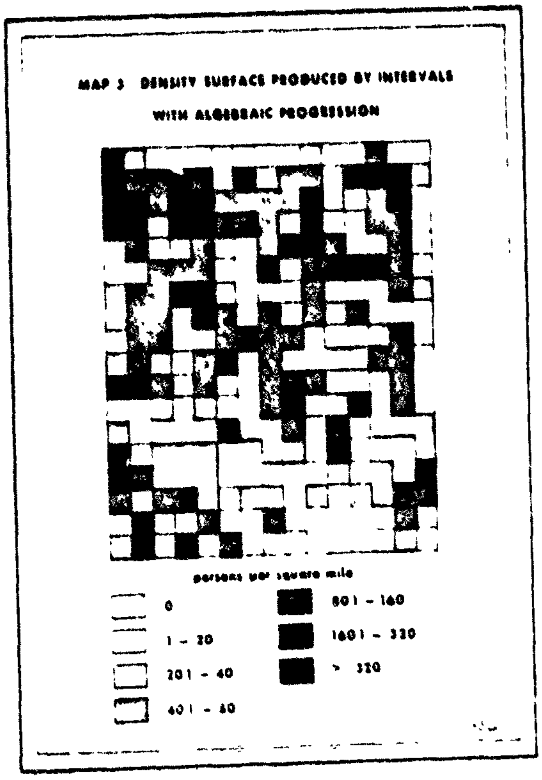
Perceptual Analyses of the RADC/Hsu Texture Measure

Experiment 1. To perform perceptual analyses with human subjects regarding similarity judgments, four choropleth maps were made showing population density patterns as scaled by four different class-interval systems (Maps 1-4). In the first experiment, ten naive human observers (cartography students) were asked to estimate the visual differences in all six of the possible double-map comparisons; e.g., Map 1 vs Map 2, Map 1 vs Map 3, etc. The allowable scale ranged from 0 (no perceptual difference) to 10 ("extremely different"). Table 5 summarizes the results in a symmetrical dissimilarity matrix of mean judged differences on the 10-point scale--standard deviations are given in parenthesis.

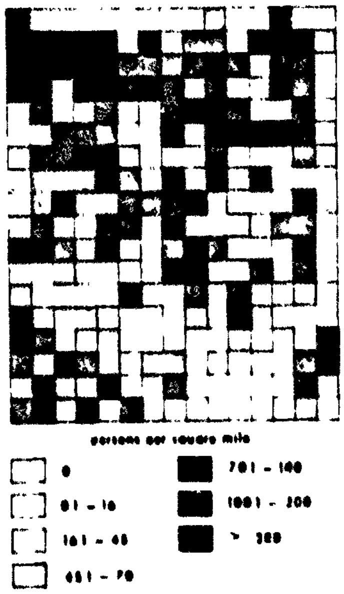

MAP 1 DENSITY SURFACE PRODUCED BY INTERVALS
HAVING EVEN AREAL DISTRIBUTION OF EACH CATEGORY
persons per square mile


MAP 2. DENSITY SURFACE PRODUCED BY INTERVALS
WITH GEOMETRIC PROGRESSION
persons per square mile

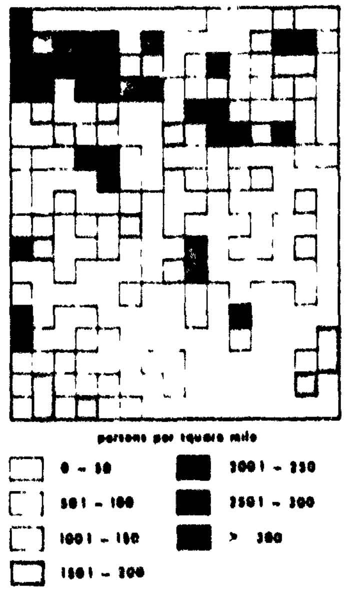

MAP DENSITY SURFACE PRODUCED BY INTERVALS
HAVING EVEN AREAL DISTRIBUTION OF EACH CATEGORY
persons per square mile
0
01 - 16
161 - 45
451 - 70
701 - 100
1001 - 200
> 200


MAP 3 DENSITY SURFACE PRODUCED BY INTERVALS
WITH ALGEBRAIC PROGRESSION
persons per square mile
0
1 - 20
201 - 40
401 - 80
801 - 160
1601 - 320
> 320

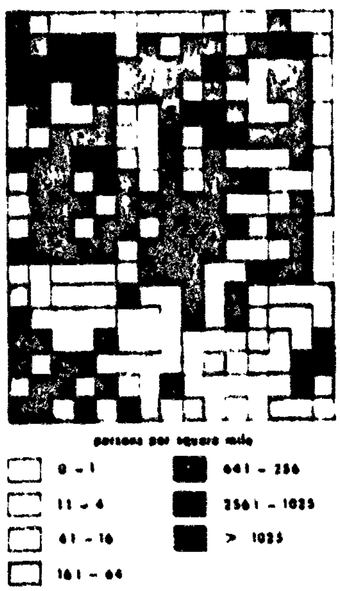
MAP 1: DENSITY SURFACE PRODUCED BY INTERVALS HAVING EVEN AREAL DISTRIBUTION OF EACH CATEGORY



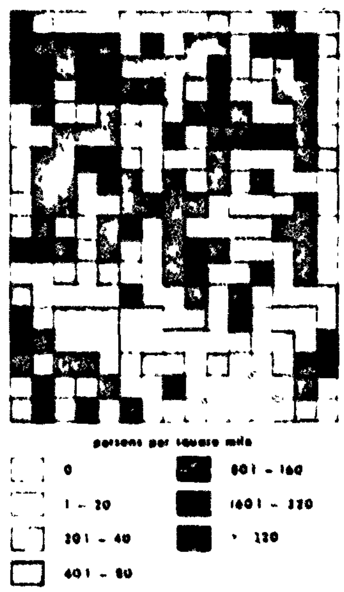
MAP 4: DENSITY SURFACE PRODUCED BY INTERVALS WITH EVEN PROGRESSION

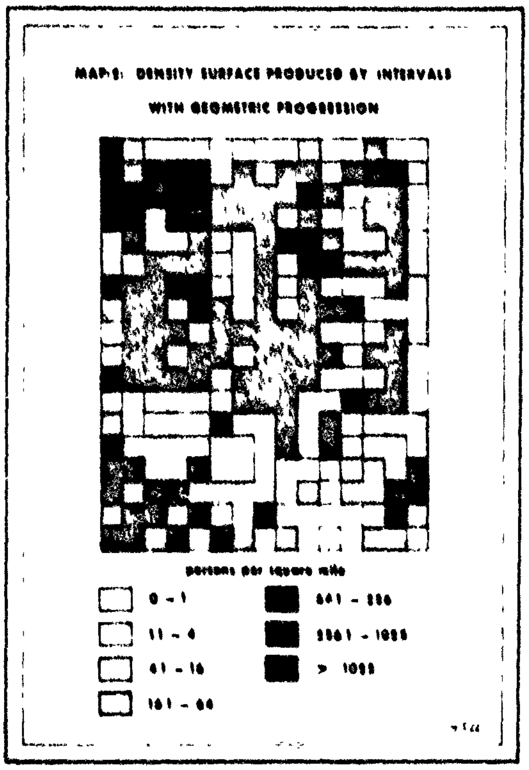


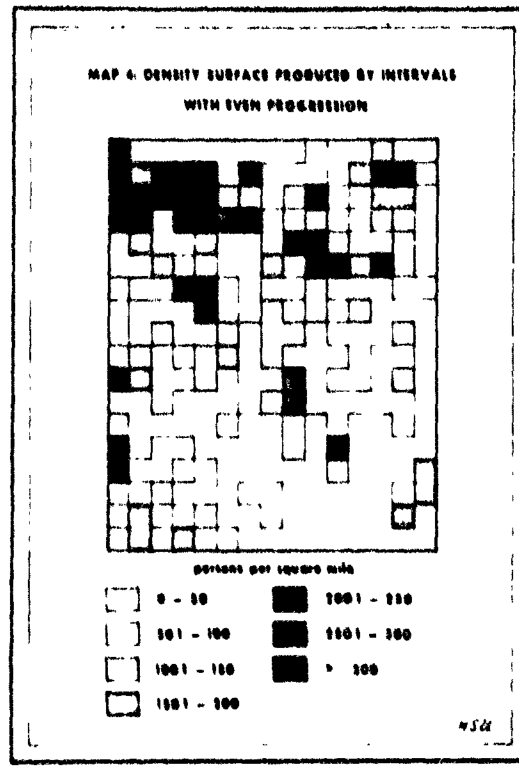
MAP 2: DENSITY SURFACE PRODUCED BY INTERVALS WITH GEOMETRIC PROGRESSION

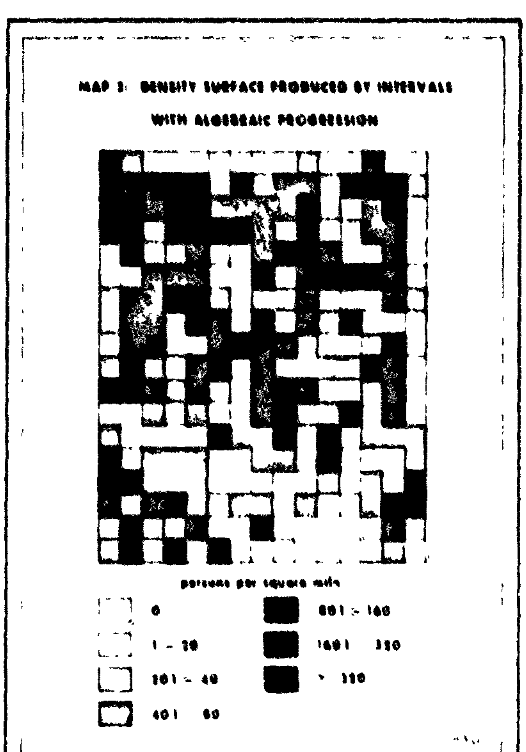


MAP 3: DENSITY SURFACE PRODUCED BY INTERVALS WITH ALGEBRAIC PROGRESSION




DENSITY SURFACE PRODUCED BY INTERVALS
WITH GEOMETRIC PROGRESSION
persons per square mile


DENSITY SURFACE PRODUCED BY INTERVALS
WITH EVEN PROGRESSION
persons per square mile


DENSITY SURFACE PRODUCED BY INTERVALS
WITH ALGEBRAIC PROGRESSION
persons per square mile

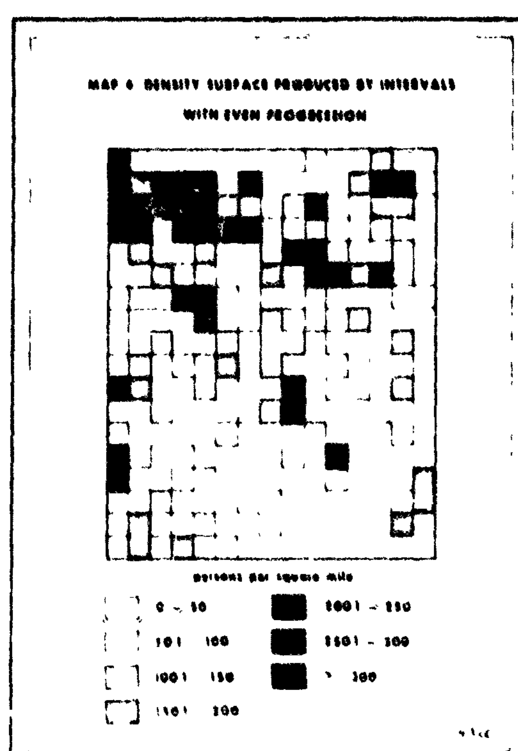

DENSITY SURFACE PRODUCED BY INTERVALS
WITH EVEN PROGRESSION
persons per square mile

TABLE 5. Dissimilarity Matrix (Symmetrical) of Mean (and Standard Deviation) Perceptual Judgments

Map	1	2	3	4
1	0	4.7 (1.6)	3.2 (2.4)	7.7 (2.2)
2		0	4.3 (1.1)	7.9 (1.3)
3			0	6.0 (1.8)
4				0

As indicated in Table 5, the Map 1 vs 4 and Map 2 vs 4 pairs were judged most different. The map pair judged least different, on average, was the Map 1 vs 3 comparison.

Such a perceptual analysis of these map-similarity judgments is indeed an analog of a statistical classification logic utilizing a minimum distance criterion. Thus, a direct comparison between this perceptual analysis and a statistical discriminant analysis based on the machine feature extractor/classifier was attempted. To provide data for such a comparative analysis, the statistical distances between the same six pairs of maps were computed using the 10 waveform parameters as response variables. Here, the texture variables were obtained from scan lines on both the x and y axes. The macro-texture of these four maps were subsequently represented by four, 10 x 13 matrices, one for each map. The numbers of scan lines correspond with the rows and columns of the choropleth maps.

Discriminant analysis is precisely the statistical technique that can be used to assess the distances among these data matrices, and to determine whether the separation between two surfaces is statistically significant (Morrison, 1976).

Table 6 shows results of this normal-model, machine solution in a symmetrical dissimilarity matrix analogous to the matrix of perceptual results given in Table 5.

TABLE 6. D^2 Distances Between Map Pairs--Normal Model Machine Solution (Macro-texture)

Map	1	2	3	4
1	0	6.64*	1.05	13.45*
2		0	2.87	16.95*
3			0	12.84*
4				0

[*$p < 0.01$ -- $F = 3.16$, df = 10,25.]

The degree of correspondence between the average human perceptual judgments and the statistical discriminant analysis of the machine data was assessed by calculating a Pearson correlation coefficient. Using the data from Tables 5 and 6, the obtained coefficient is very high indeed ($r = 0.95$).

Experiment 2. Since we developed a texture feature extractor capable of analyzing the micro-texture of individual pixels using a (3 x 3) moving grid, we proceeded to determine how closely this 17-variable system correlated with human perceptual judgments. In addition, we wanted to know whether we could use only 3-5 of the 17 variables in this system to achieve a comparable level of performance. While such a 3-5 variable system would obviously result in reduced computer time (see below), it also is interesting to recall that Richards (1978) has reported that 3-5 "primaries" can produce texture metamers in visual matching of "random-dot" patterns by human observers.

To compensate for the potential loss of power in the feature extractor by using only 3-5 variables, and/or to better reflect the characteristics of the distributions of digitized image information (cf., Hsu, 1978), we developed a non-linear classifier based on the stable distribution model which is still capable of ultimately employing the Mahalanobis D^2 as a quantitative distance measure (Hsu and Klimko, 1979). Compared with the normal distribution model, the stable distribution has four (instead of two) basic parameters, and is capable of handling both non-normal as well as normal distributions. Experiments with this stable model classifier have shown that the needed number of texture variables for a machine solution comparable to that obtained with the original, 17-variable normal model classifier is typically drastically reduced to about 3: e.g., stable distributions of the mean, first-neighbor contrast, and second-neighbor contrast. As a result, the data processing time for the same number of points (256 x 256) was reduced to 15 minutes from 90 minutes of CPU time using standard FORTRAN.

To assess the degree of correspondence between the human visual system and this newly developed machine processing system we replicated the perceptual test discussed in Experiment 1 utilizing the same four choropleth maps, but 10 different, naive observers (again, graduate and undergraduate Geography volunteers at SUNY-Binghamton). The judgments in replications 1 and 2 were quite comparable (r for first and second replication means = 0.92), and we pooled the set of 20 human observations to yield the mean (and standard deviation) results shown in Table 7, which is directly comparable to Table 5.

TABLE 7. A Symmetric Dissimilarity Matrix for Perceptual Judgments Based on 20 Human Observers (0-10 Scale)

Map	1	2	3	4
1	0	4.72 (1.46)	2.98 (1.82)	7.30 (1.83)
2		0	4.12 (1.68)	7.70 (1.37)
3			0	6.68 (1.68)
4				0

Comparable to Experiment 1, we also computed the distance between map pairs using the stable Mahalanobis classifier with only three, tone-texture variables: mean density, 1st neighbor contrast and 2nd neighbor contrast. Since individual matrices, instead of a pooled dispersion matrix, was utilized in the analysis, the Mahalanobis D^2 distances in the dissimilarity matrix are not symmetric (see Table 8). The upper diagonal D^2 values represent row to column comparisons and the lower diagonal D^2 values indicate column to row comparisons. The differences may be analogous to influences of orientation on human judgments, but these matters deserve further study. In these studies, the maps were oriented for human judgments as they are presented on these pages. However, to correlate this set of machine outcomes to the perceptually-judged scores, we initially employed the upper off-diagonal stable distribution solution. Other aspects of the asymmetric machine solution pattern will be considered later.

TABLE 8. The Asymmetric Dissimilarity Matrix (D^2) From the 3-Variable Feature Extractor and Non-linear (Stable) Classifier Machine Solution

Map	1	2	3	4
1	0	1.9	0.3	3.0
2	1.7	0	0.6	4.3
3	0.5	0.7	0	3.3
4	4.3	12.5	6.0	0.7

A product-moment correlation of $r = 0.96$ was obtained using the upper diagonal D^2 values in Table 8 and the average of the 20 human judgments (Table 7). Using the normal distribution machine solution for these four maps (Table 6), and the means of the 20 human judgments, the correlation is 0.98. The rank order correlation between the normal distribution machine solution and the human observations is perfect, as is the rank order correlation between the upper and lower diagonal stable distribution solutions. In terms of rank order, the normal solutions and the human judgments are very closely (but not perfectly) related to the upper and lower diagonal stable distribution solutions. Clearly, the outcome of our 3-variable feature extractor/classifier also is highly correlated with human judgments, and provides another indication that our texture-tone machine analysis method may provide some insight into the intricate relationships between purely machine-based and perceptually-based pattern recognition systems.

Experiment 3. (Free-run/Minimum Stress Model) In the next experiment, we decided to further examine the relationship between the 20 human perceptual judgments and the two machine solutions (normal and stable distribution models), and to determine how the machine solutions relate to a two dimensional space derived by the non-metric, multi-dimensional scaling method recently by the Psychometrics Laboratory at the University of North Carolina (cf., Takane, Young and deLeeuw, 1977).

First, we converted the entire three sets of data (human, normal model and upper-diagonal stable model) into z-scores based on a common scale of 0-10 as used by the human observers. This was accomplished directly for the judgments of each individual human observer, and by considering the D (not D^2) values of each machine solution, and then assigning appropriate values relative to a maximum D = 10. These standardized dissimilarity scores are presented in Figure 3, with the x-coordinate as map pairs and y-coordinate as the z-scores. Standard errors for the mean human judgments ranged between 0.09 and 0.21 on this z-scale. The similarities among configurations of these standardized dissimilarity distances between map pairs by the three solutions, as expected by the correlations already reported, is quite striking.

To determine a framework in which the human and machine "judgments" of similarity among these map pairs might be viewed, we decided to use non-metric scaling procedures (cf. Hake and Rodman, 1966). Employing the multi-dimensional scaling technique developed by Takane, Young and de Leeuw (1977), we obtained a two-dimensional model using the dissimilarity matrices generated by each of the 20 human subjects, plus those obtained from four machine solutions defined by the normal model as well as by the upper diagonal, lower diagonal, and upper plus lower averages of the stable model.

FIGURE 3: Dissimilarity Patterns of Population Density Maps: Human Subjects versus Machine Solutions

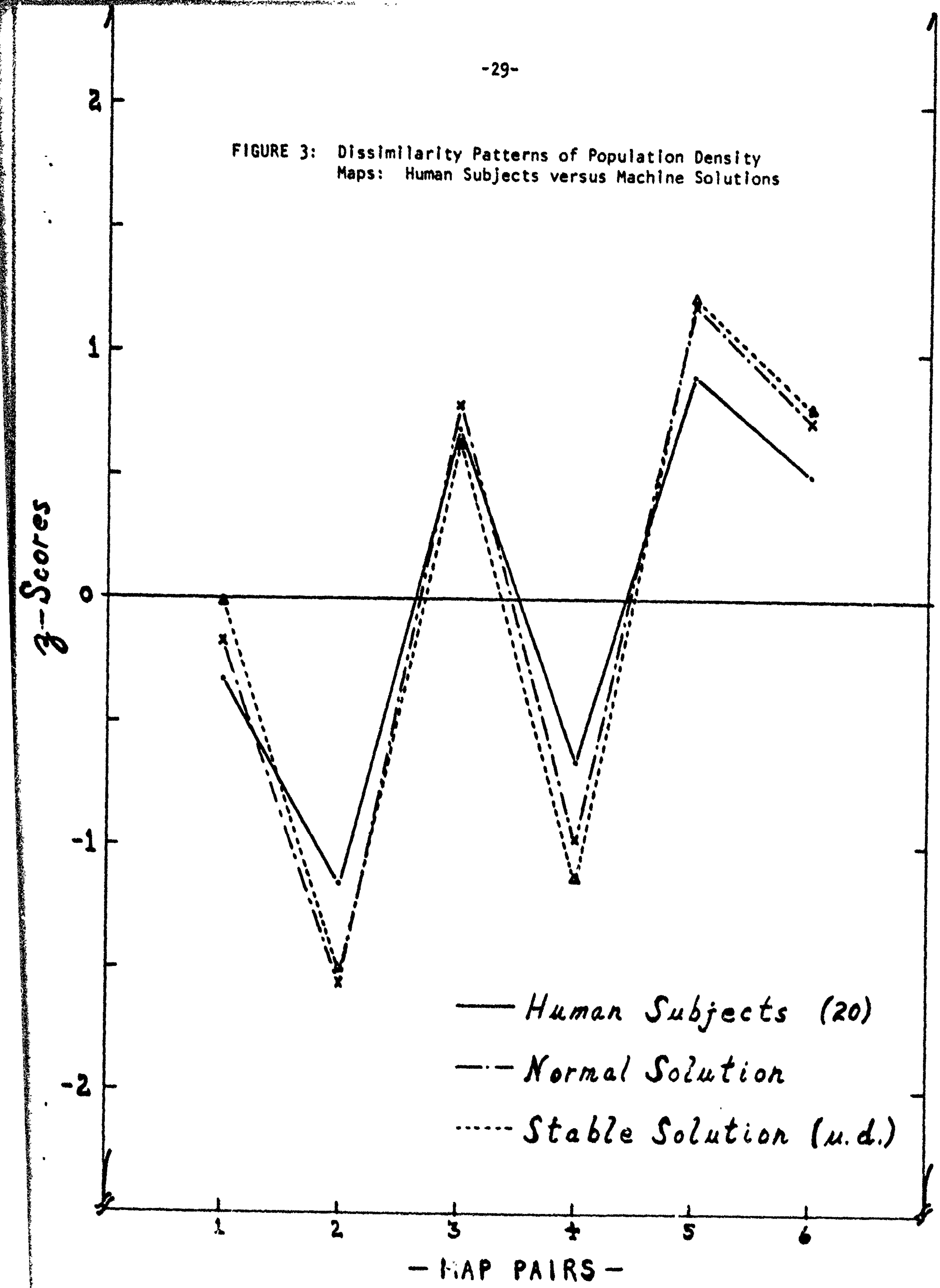
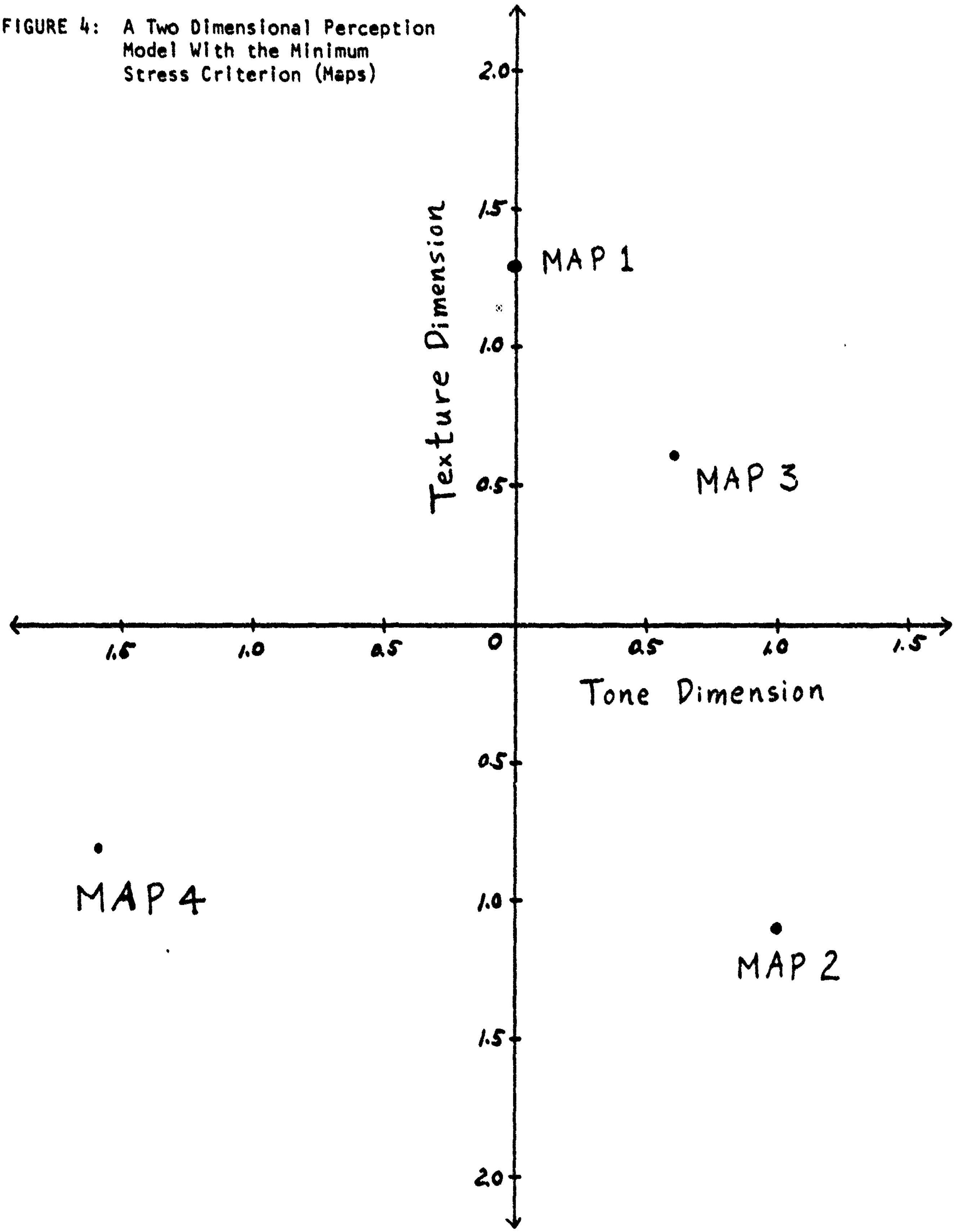


FIGURE 4: A Two Dimensional Perception Model With the Minimum Stress Criterion (Maps)



The two dimensional model derived by this alternating least squares method using the 24 dissimilarity matrices as defined above is presented in Figure 4. Dimension I (the x-axis) orders our four map stimuli as follows: Map 4, Map 1, Map 3 and finally Map 2. Since Map 4 is lightest, and the average greytone becomes darker following the map order along this dimension, it seems reasonable, at least tentatively, to label Dimension I as a "tone" dimension.

Dimension II (the y-axis) of the derived stimulus space orders our maps as: Map 1, Map 3, Map 4 and finally Map 2. Since these maps were created from the same data set by systematically varying the class-interval used, we are able to describe the nature of each pattern quite accurately (cf. Hsu, 1974). For instance, Map 1 was produced by requiring that each class have the same areal distribution (equal area system); therefore, among all four maps, Map 1 should have the highest neighbor contrasts or the highest frequency of greytone changes between neighboring cells. In this regard, Map 3 is almost the same as Map 1 since their class-interval systems vary only slightly. In contrast, Maps 2 and 4--at the "other end" of Dimension II _re_ Maps 1 and 3--used class-interval systems which necessarily resulted in greytone patterns which produce relatively little contrast between and among neighboring cells. Thus, comparatively, the near neighbor contrasts in Maps 2 and 4 are considerably less than those displayed in Maps 1 and 3, and may be considered perceptually less "busy" or texturally less complex. Dimension II might reasonably be considered a "texture" dimension. However, it should be noted that it is doubtful that texture can be fully described, _in general_, along a single dimension (see above).

The individual differences scaling model employed enables us to examine how each of the 24 dissimilarity matrices (20 human observers, plus 4 machine solutions) weighted the importance of the two derived stimulus dimensions. All 24 of these weight vectors are plotted in Figure 5, with human observations depicted by dots, and the four machine solutions identified appropriately; the two coordinates represent the weights on Dimension I ("tone") and Dimension II ("texture"), respectively. Table 9 lists furthermore R-squared values of each individual in relation to the derived stimulus-dimension model.

From Figure 5 and column 1 of Table 9, it can be noted that 60 percent of the individual decisions are distributed very nearly along an arc of radius 1.0 in this weighting space. Any point on such an arc represents a perfect fit to the two dimensional "tone-texture" model derived; the further a point is from this arc, the greater the stress (cf. Takane, Young and de Leeuw, 1977) of that individual's judgment for the model. Clearly, there are distinct individual differences of the weightings in this model space: whereas 60% of the subjects show very good fit, 15% show good fit, another 10 percent show moderate fit, and the remaining 15 percent do not fit the model well at all. It is worthwhile to note that all of the four machine solutions have a perfect fit. Interestingly, 35 percent of the human observations tended to weigh the "tone" dimension somewhat more than the "texture" dimension; 40 percent of the subjects reverse the pattern; 20% of the subjects weighted the tone dimension equal with the texture dimension, and finally, 5% of the subjects used neither dimension in the discrimination of map surfaces. Of the four machine solutions included in the creation of the "tone-texture" model presented, only one solution (the normal model) used the texture criterion more than the tone dimension, whereas three of the stable distribution solutions primarily used the tone criterion (Table 10, column 1).

FIGURE 5: A Two Dimensional Fixed Model With Computed Tone-Texture Parameters (Maps)

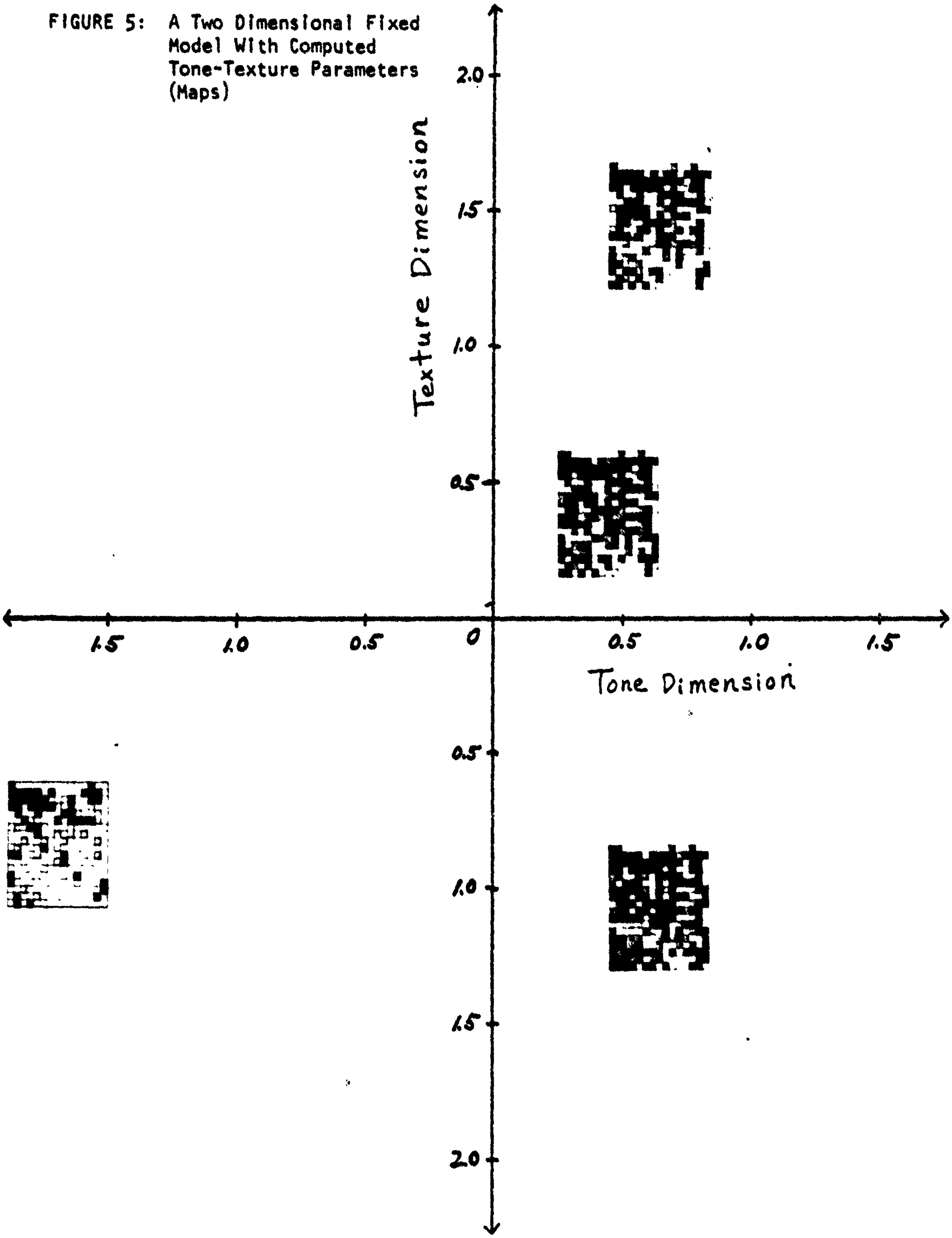


TABLE 9. Individual Differences (Goodness-of-Fit) in Relation to Two Models

	Map 20 + 4 Column I: Model Determined by the Minimum Stress Criterion R^2		Map 20 + 4 Fixed Column II: Model Fixed With Computed Feature Statistics Tone-Texture Parameters R^2	
1.	0.831	II	0.206	IV
2.	0.817	II	0.457	IV
3.	0	IV	0	IV
4.	1.00	I	1.000	I
5.	0.41	IV	0.699	III
6.	1.000	I	1.000	I
7.	0.999	I	0.922	I
8.	0.999	I	0.999	I
9.	0.690	III	1.000	I
10.	0.226	IV	0.526	IV
11.	0.877	I	0.983	I
12.	0.690	III	0.998	I
13.	1.000	I	0.986	I
14.	0.806	I	0.994	I
15.	1.000	I	0.994	I
16.	0.868	I	0.826	II
17.	0.809	II	0.457	IV
18.	0.945	I	0.994	I
19.	0.891	I	0.988	I
20.	1.000	I	0.999	I
21. Normal	1.000	I	1.000	I
22. UD STABLE	1.000	I	0.986	I
23. LD STABLE	1.000	I	0.986	I
24. $\bar{X}$ STABLE	1.000	I	0.986	I

Determined

I	II
-0.01	1.30
0.99	-1.10
0.63	0.64
-1.61	-0.83

Fixed

I	II
0.64	1.45
0.65	-1.02
0.42	0.39
-1.72	-0.83

I: > 0.85
II: 0.84 – 0.71
III: 0.70 – 0.50
IV: < 0.50

TABLE 10. The Weighting Patterns: Tone Versus Texture Criterion (Maps)

	Column I: Determined Minimum Stress Model		Column II: Fixed Model	
	20 Subjects	Computer Solution	20 Subjects	Computer Solution
1. Tone Oriented	7 (35%)	3	9	4
2. Even Tone & Texture	4 (20%)	1	1	
3. Texture Oriented	8 (40%)	1	9	
4. Neither Tone nor Texture	1 (5%)		1	
Total	20	4	20	4
	Average Tone: 0.66 Texture: 0.55		Average Tone: 0.70 Texture: 0.29	

Of course, ideally we would like to be able to establish a priori models of stimulus dimensions based structly upon either human or machine solutions alone, and then determine how individual results relate to such models. We will discuss this approach in Experiment 4. In addition, the generality of our findings must be more fully explored. For instance, the four maps employed in these studies were created by varying class-intervals and providing each stimulus with a total of seven greytone values. In Section D we will investigate patterns derived from real-world images which necessarily have different levels and numbers of levels of greytone values. Furthermore, an additional 40 human observers will be examined to determine if and how different perceptual models or dimensional weightings may appropriately characterize different sub-populations of subjects and/or viewing conditions.

Experiment 4 (Fixed Model). While the previous experiment (3) described the individual differences in relation to a two dimensional stimulus model determined by the use of a minimum (over-all) stress criterion, in this experiment (4) we will discuss the individual responses in relation to a fixed tone-texture model with parameters computered for the digitized image data information. Specifically, we used the overall average density of each map to quantify the "tone" dimensions, and the average of the 1st neighbor and 2nd neighbor contrast statistics to quantify the "texture" dimension.

The results of this analysis with 20 human subjects plus the same four computer solutions used in experiment 3 are listed in Column II of both Table 9 and Table 10. The graphic presentations of this model and the individual solutions with respect to the model are given in Figures 6 and 7 respectively.

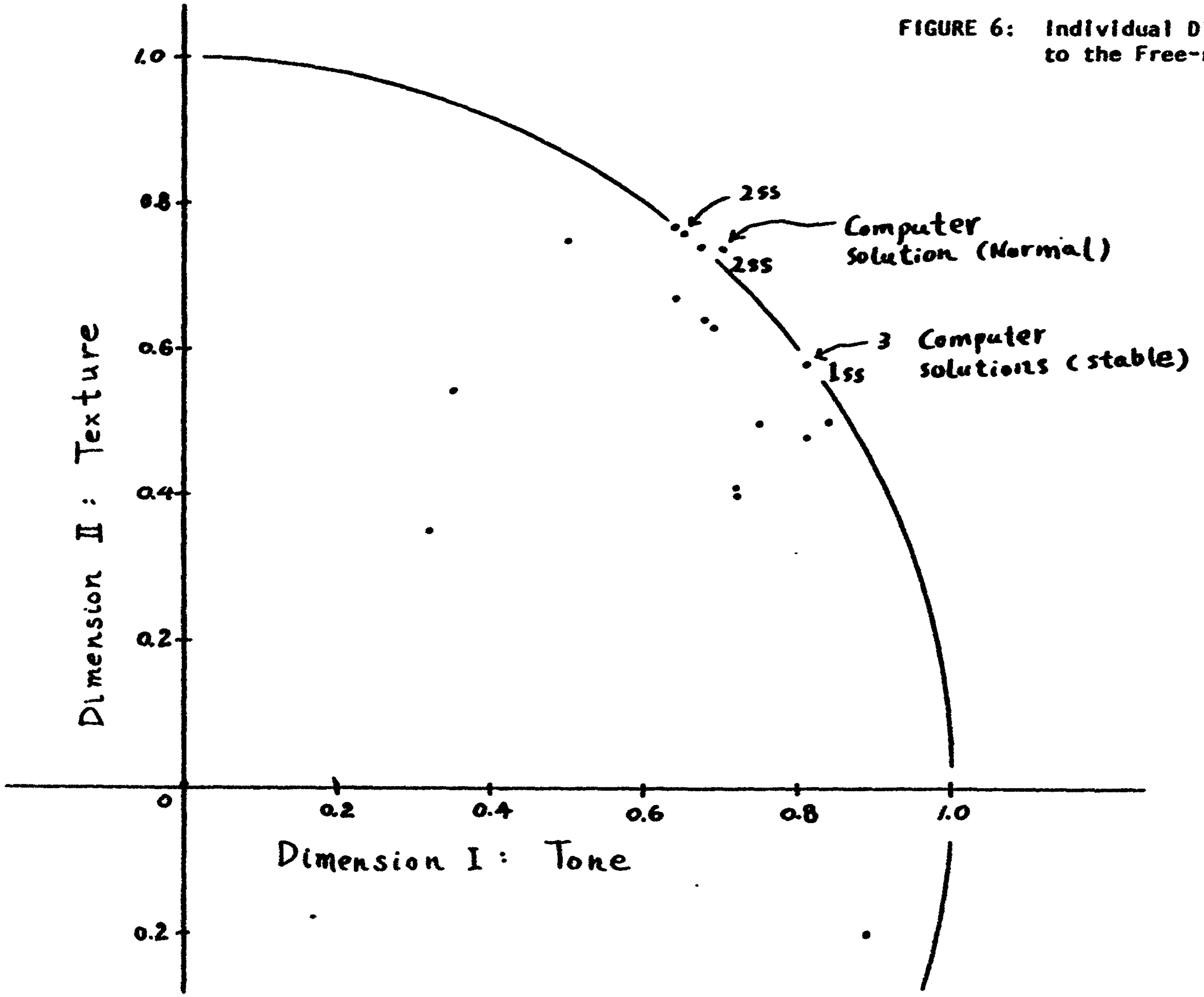
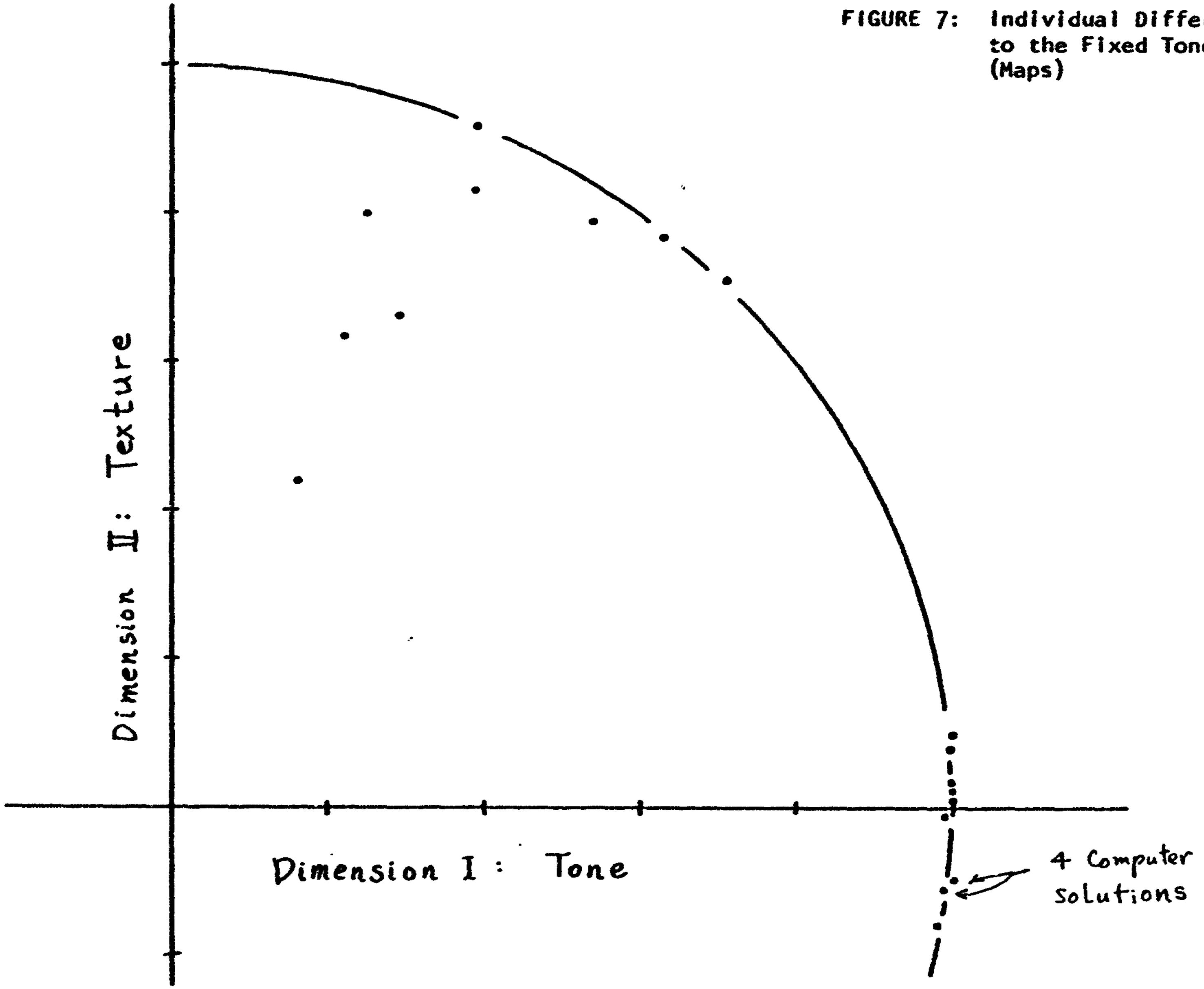


FIGURE 6: Individual Differences With Respect to the Free-running Model (Maps)

FIGURE 7: Individual Differences With Respect to the Fixed Tone-texture Model (Maps)



First of all, it should be pointed out that the minimum stress criterion solution (Experiment 3) yielded almost the same stimulus dimension space as specified by the fixed model with only a very slight difference in the position of Map 1 on the tone dimension. This discrepancy is probably insignificant since the apparent overall brightness of Maps 1, 2 and 3 is essentially the same.

The overall pattern of individual differences in map discrimination between the minimum stress model and this fixed model are very similar (compare Column I and Column II in Table 9 and Table 10). The results of Experiment 3 and Experiment 4 imply that: (1) the Hsu texture measurement with parameters of the mean tone and the 1st and 2nd neighbor contrasts is indeed perceptually-based, (2) the human observers tended to use both the tone and texture dimensions in the discrimination of patterns created by greytones, and (3) in general, the machine solutions weighted the tone information much heavier than the texture information, whereas the humans weighted the tone dimension only slightly heavier than the texture dimension (see Table 10, re the average weights).

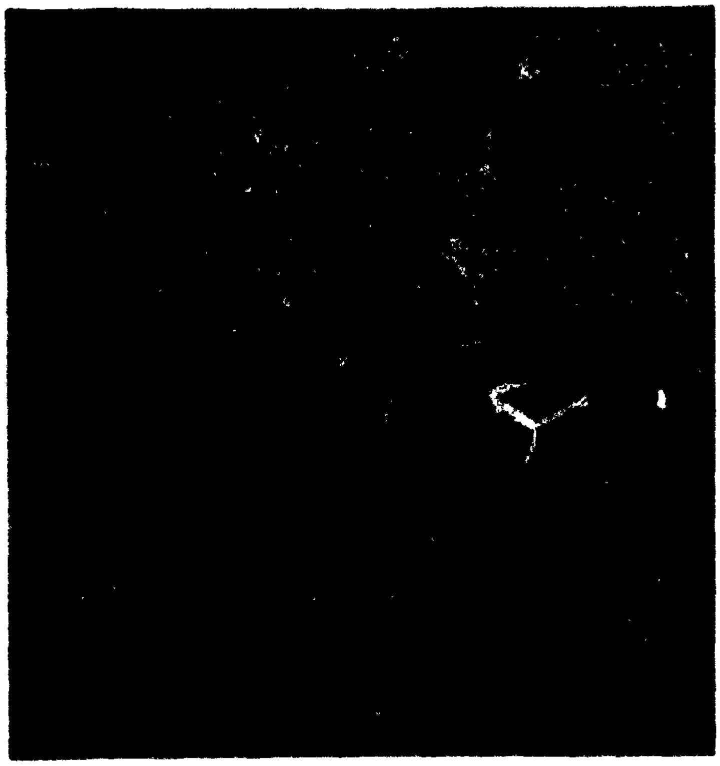
D. TEXTURE PERCEPTION OF REAL-WORLD TERRAIN PATTERNS

In Section C, we described the perception of choropleth maps by human subjects and its relationship with machine solutions based on the RADC/Hsu texture measurements. As described earlier these choropleth maps were created from a common data set by varying the class-interval system; and therefore, the textural patterns were derived from only the spatial distribution of tones.

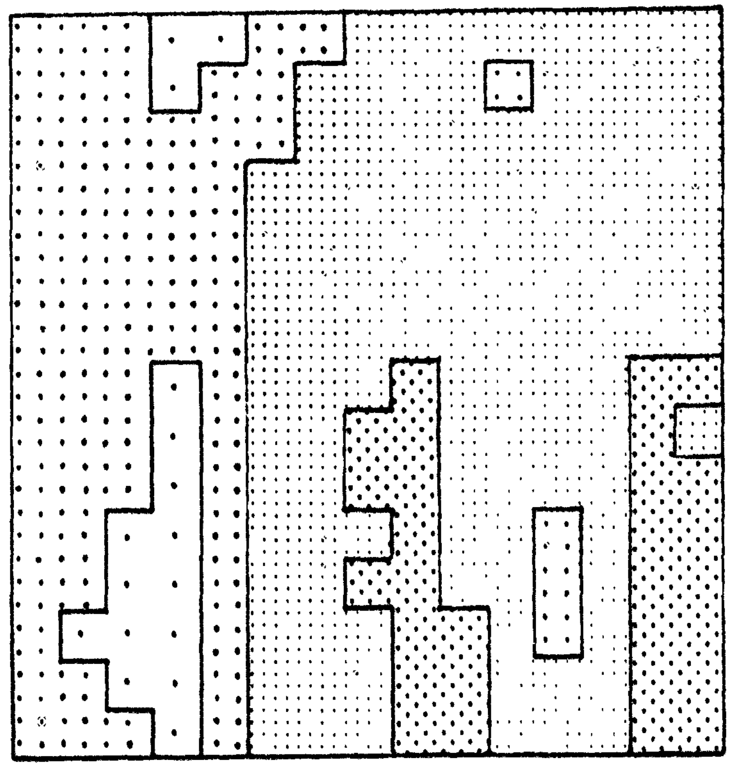
In this section, we will discuss texture perception of image patterns derived from real-world terrain patterns including vegetation, cultivated fields, edgepave (asphalt), and pavement (concrete). Compared to the choropleth maps, the textural patterns of terrain types are much more complicated since they involved simultaneously with contrasts in both tone and texture levels. For instance, the tone level of vegetation is much darker than that of pavement, and furthermore, there is texture complexity in both vegetation and pavement. These patterns of terrain types are given in Figures 8, 9, and 10, showing the six image pairs used in our perceptual tests. The following sections describe our analyses of texture perceptions with these terrain patterns. It should be noted that the methodologies, including the derivation of visual dissimilarity scores and stimulus dimension models for the following experiments are the same as those used in previous experiments (3 and 4).

Experiment 5 (Free-run or Minimum Stress Model). In this analysis of the texture perception of choropleth representations of terrain patterns, we used 40 subjects to determine the visual distances among the terrain image pairs (Figures 8, 9 and 10). Similar to the human judgments versus the machine solution related to the perception of population maps (Figure 3), we plotted the mean normalized z-scores of perceptual differences of 40 human observers against the machine solution (D^2 derived from the Hsu measurement with these three tone-texture variables: mean density, 1st neighbor contrast and 2nd neighbor contrast) in Figure 11. Compared to Figure 3, Figure 11 expresses a greater variation in the human judgments of differences in terrain patterns than in perception of the maps; however, the general agreement among z-score patterns still exists.

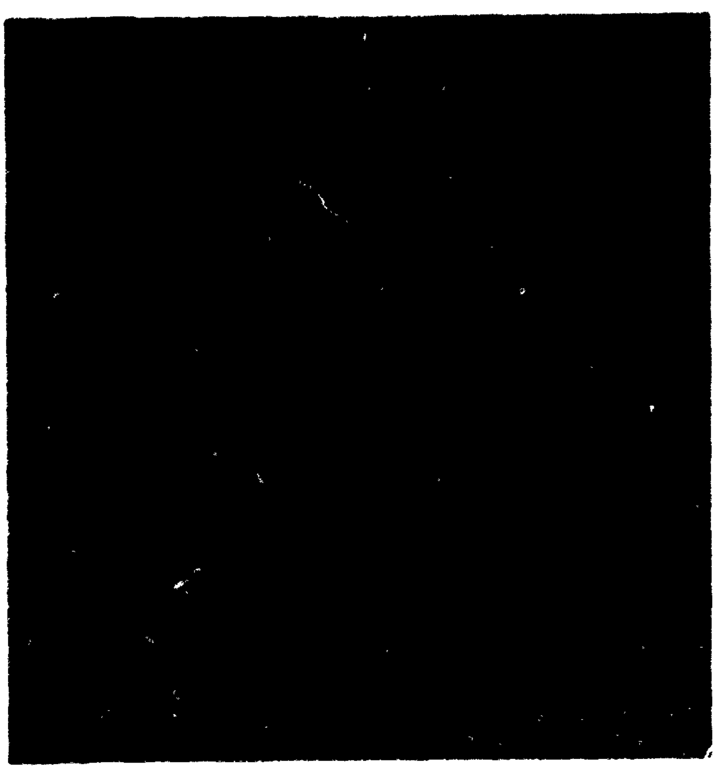
The two dimensional model derived by the "free-running," minimum stress criterion using the 40 dissimilarity matrices plus one machine solution (stable model) is presented in Figure 12. Dimension I (the x-axis) orders our terrain types stimuli as follows: Vegetation, Cultivated Field, Edgepave and Pavement. This order clearly establishes a "tone" dimension.



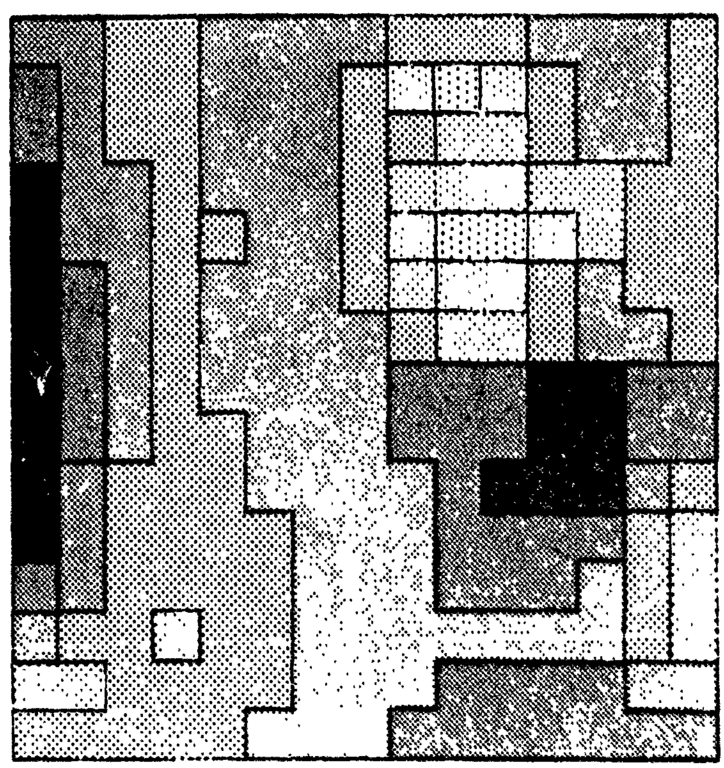
VEGN



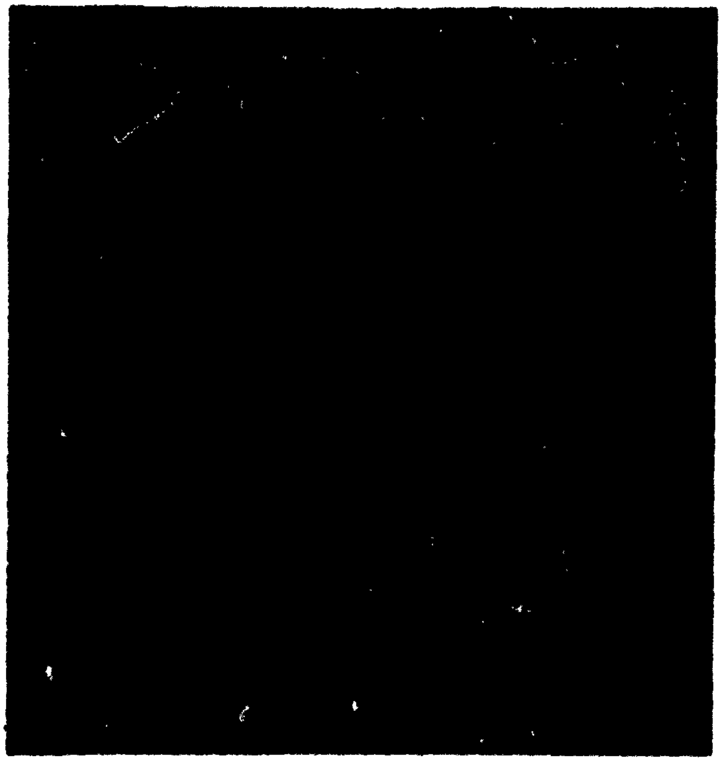
PAVE



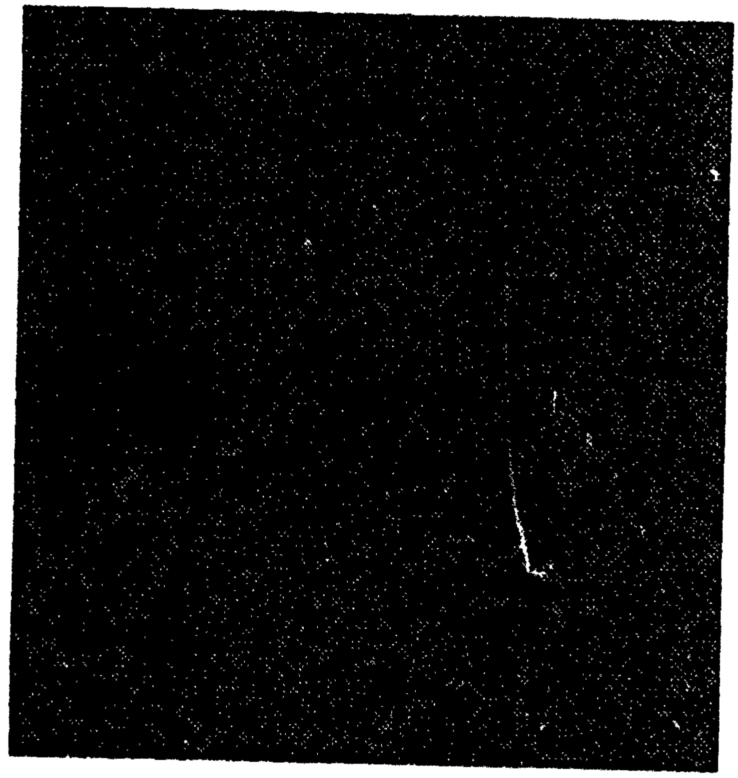
VEGN



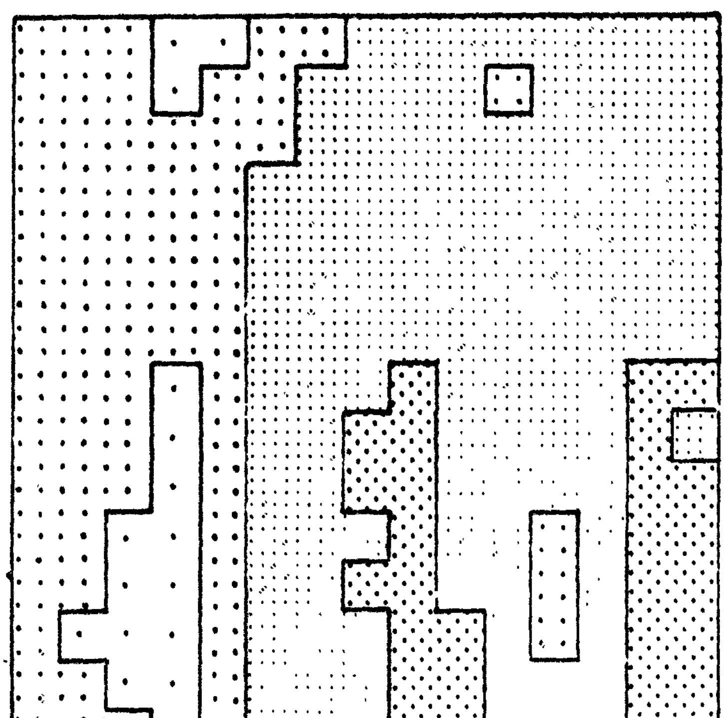
EDPV



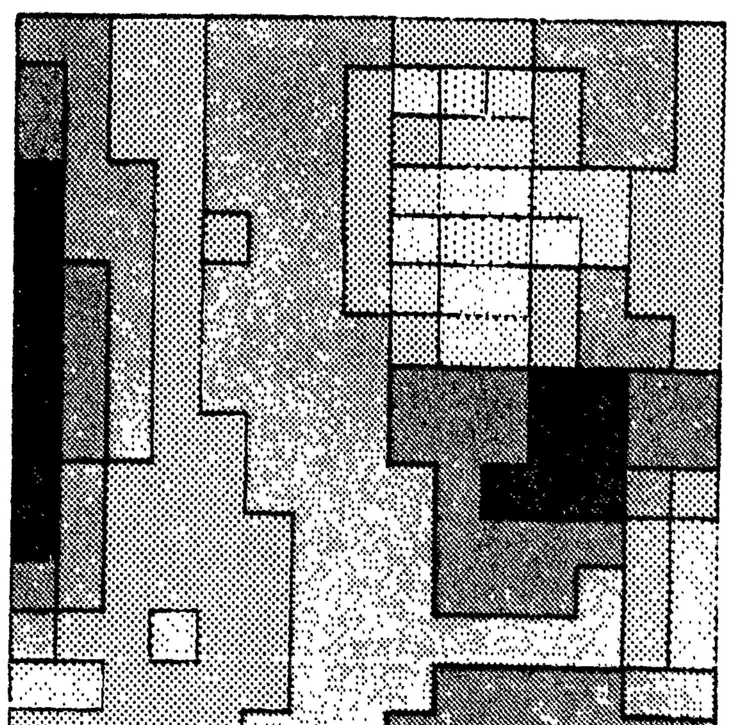
VEGN



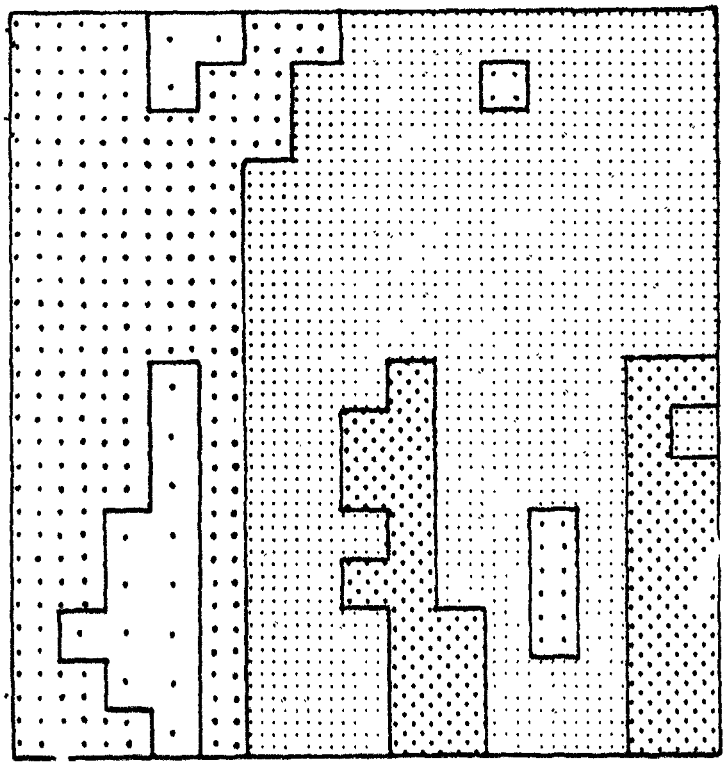
CFLD



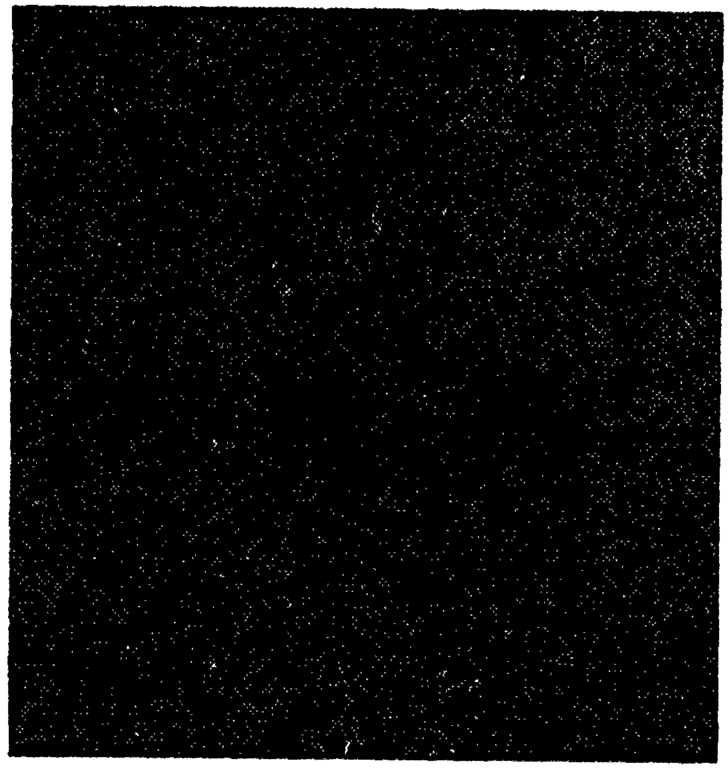
PA/E



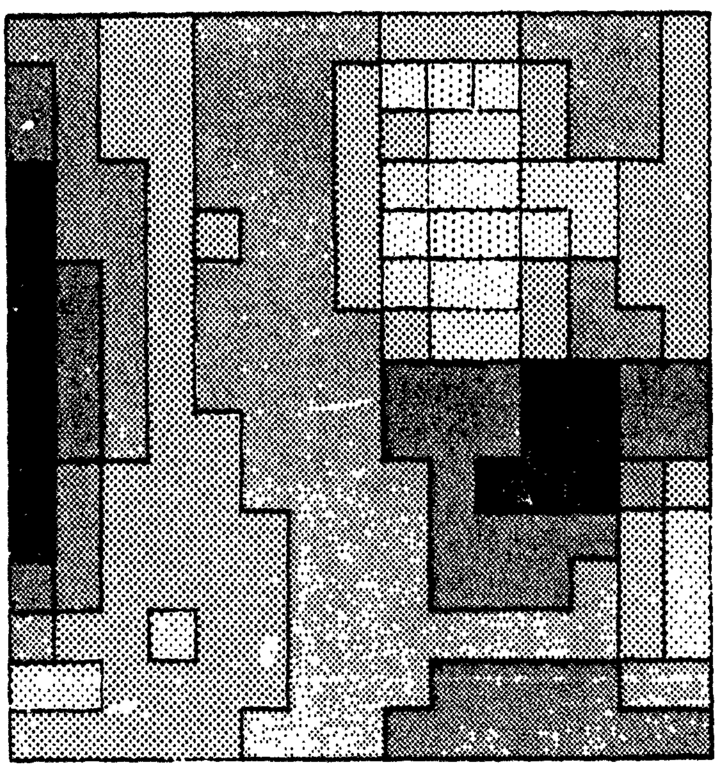
EDPV



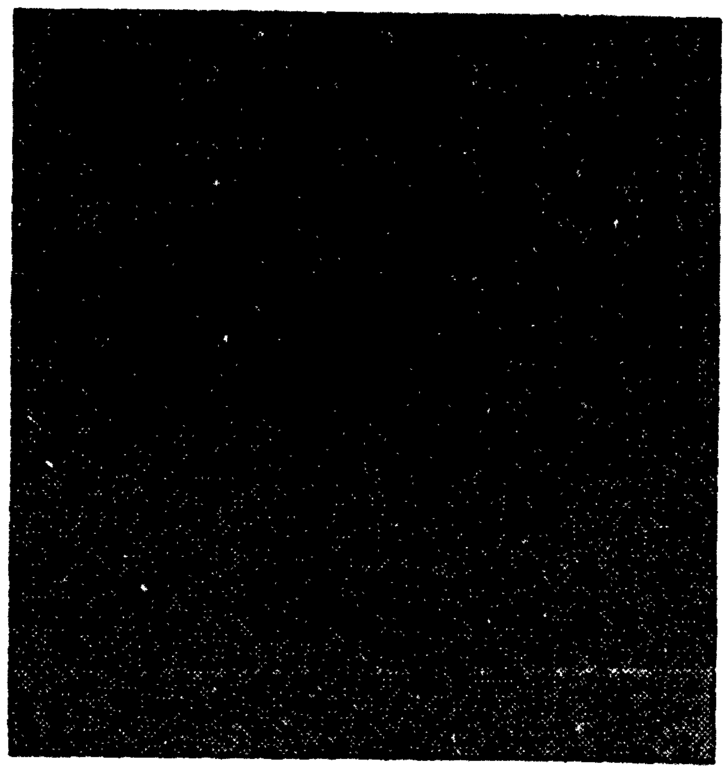
PAVE



CFLD



EDPV



CFLD

FIGURE 11: Dissimilarity Patterns of Terrain Types: Human Subjects Versus a Machine Solution

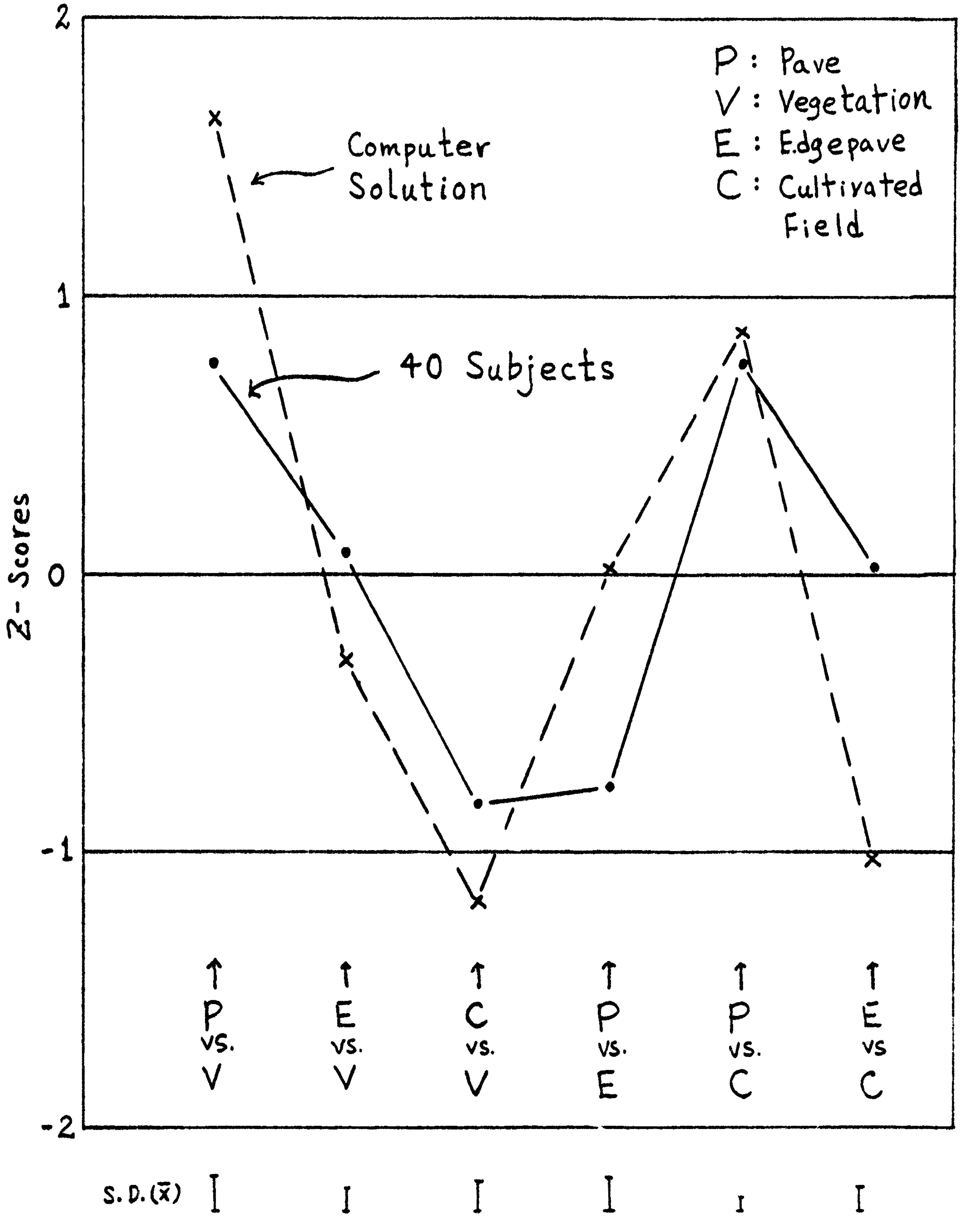
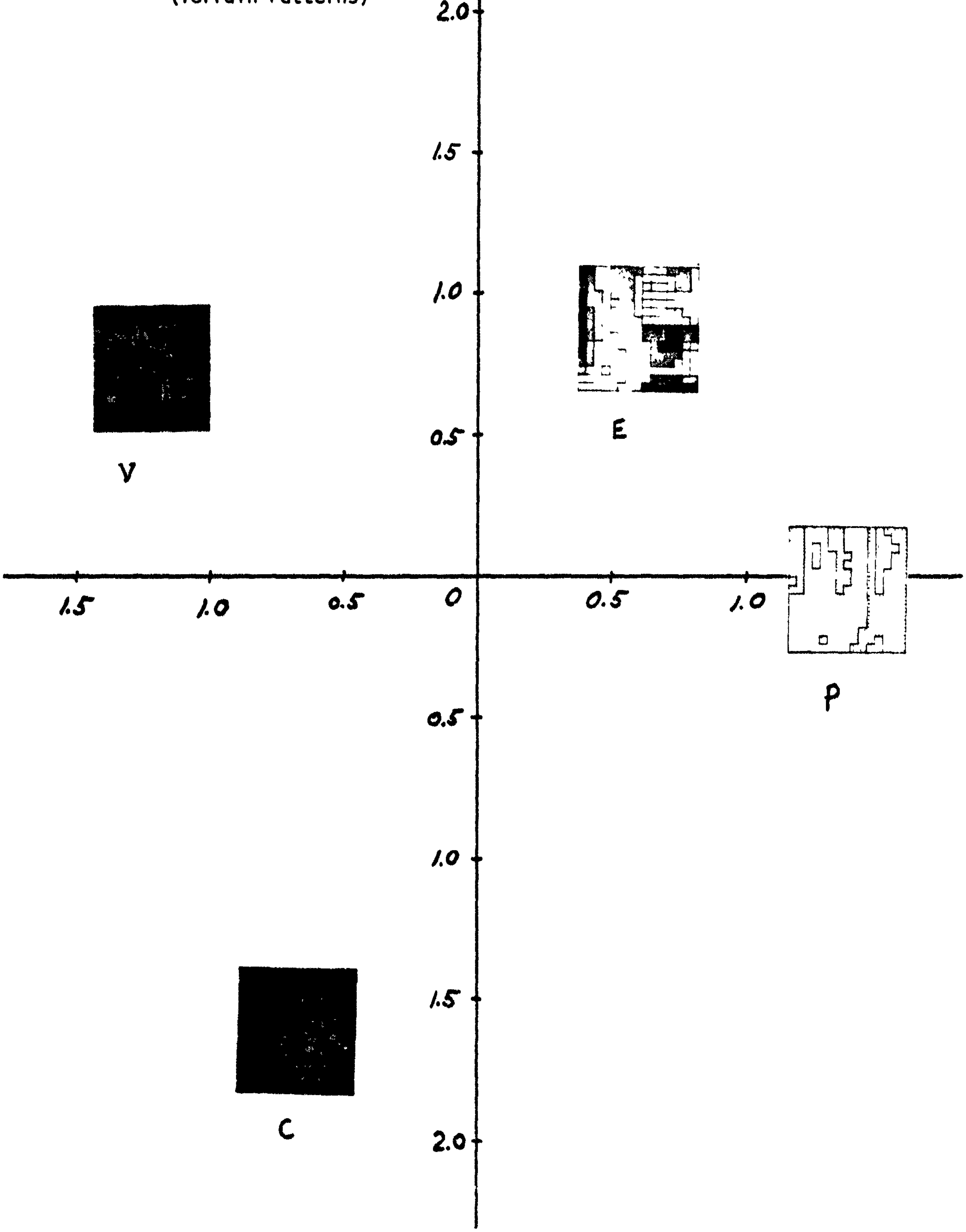


FIGURE 12: A Two Dimensional Perception Model With The Minimum Stress Criterion (Terrain Patterns)



Dimension II (the y-axis) of the stimulus space orders the terrain patterns as: Edgepave, Vegetation, Pavement and then Cultivated Field. Without the vegetation, this dimension would appear to be a "texture" dimension. With vegetation, this dimension maybe representing a combined "texture plus structure" dimensions; i.e., while pavement appears more texturally complex than vegetation, vegetation maybe viewed as having more "character" than pavement in terms of a "structural" dimension.

Individual differences in this model are shown in Column I of Table 11 and Figure 13 with respect to R^2 values. In this context, 42.5 percent of the 40 observers display a very good fit, 35 percent a good fit and the remainder (22.5 percent) provide a poorer fit or no fit al all. The data in Column I of Table 12 show further that most of the individuals (80 percent) weighted the tone dimension most heavily in judging the differences among these image pairs.

The machine solution in this model indicates only a moderate degree of fit with an R^2 of 0.74. This is understandable because this free-running model is structured according to "tone" and "texture plus structure" dimensions fixed by human judgments, whereas the machine solution was fixed purely on tone (brightness) and texture (neighbor contrasts) dimensions without any "structure" parameters in the feature extractor. Similar to the majority of the human observers, the machine solution weights the tone dimension heavier than the other dimension.

<u>Experiment 6</u> (Fixed Model). Since in Experiment 5, we were not able to establish a clear-cut stimulus dimension for texture, we decided to fix the model with the tone and texture parameters derived from the feature statistics defined by digital information regarding the mean density and the neighbor contrasts. This fixed model is given in Figure 14, using mean density as the "tone" dimension, and the average of the 1st neighbor contrast and the 2nd neighbor contrast as the "texture" dimension, just as in Experiment 4 with the population maps.

FIGURE 13: Individual Differences With Respect to the Free-running Model (Terrain Patterns)

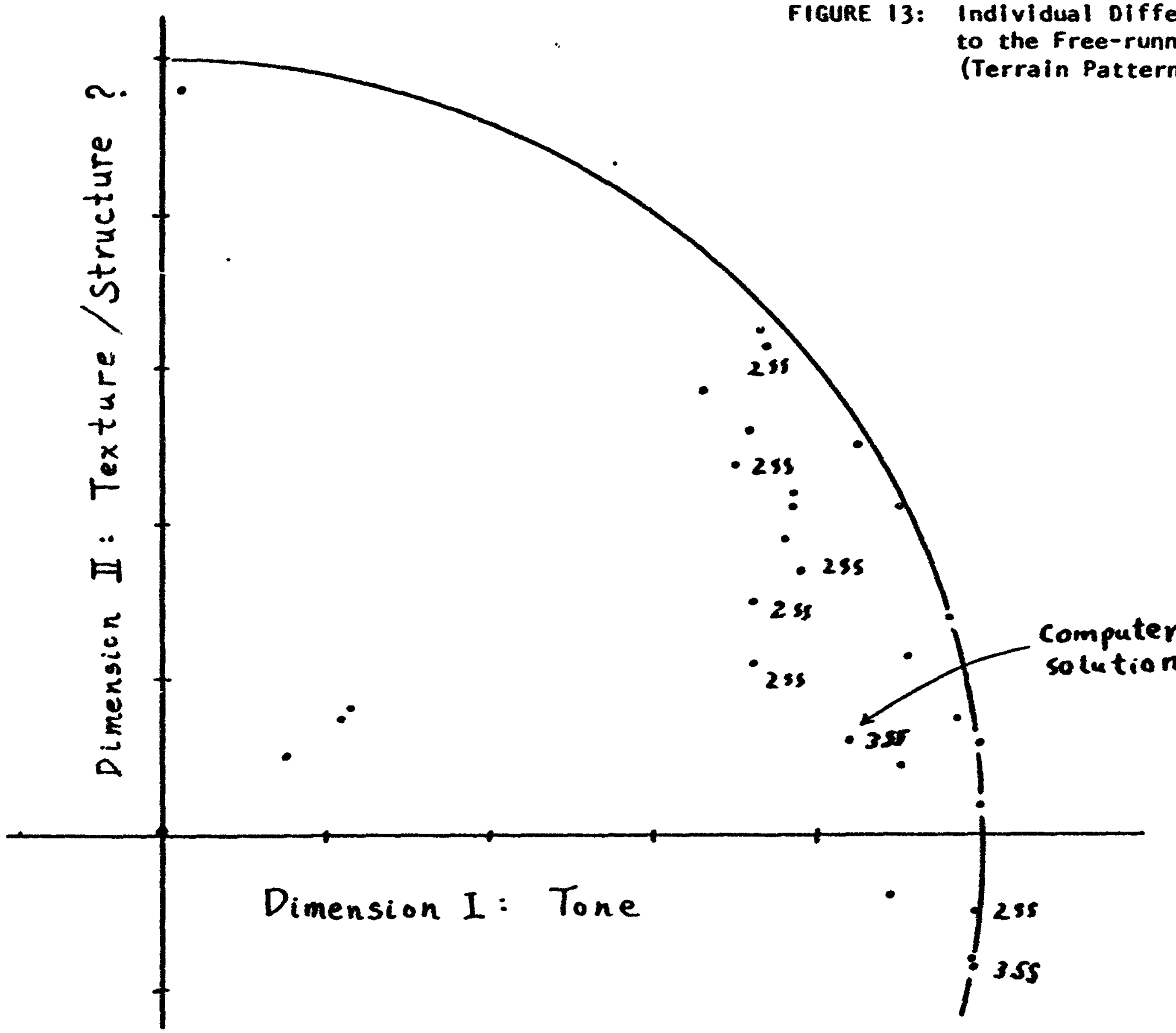
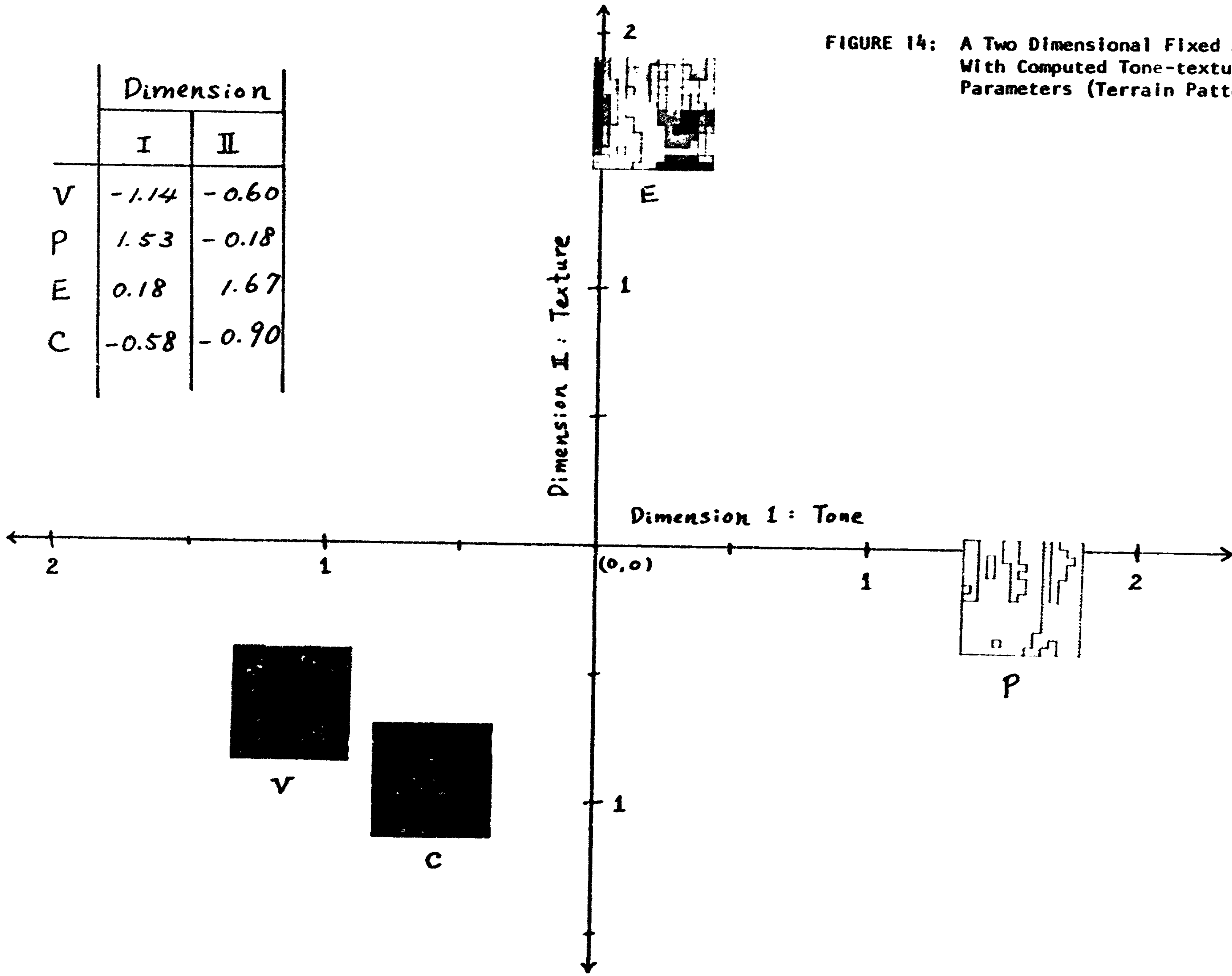


FIGURE 14: A Two Dimensional Fixed Model With Computed Tone-texture Parameters (Terrain Patterns)

	Dimension I	Dimension II
V	-1.14	-0.60
P	1.53	-0.18
E	0.18	1.67
C	-0.58	-0.90



The individual differences scaling model employed then enabled us to examine how each of the 40 subjects weighted the importance of these two fixed stimulus dimensions. The results are given in Column II of Table 11 and Figure 14 showing: 52.5 percent of the subjects displaying a very good fit (R^2 greater than 0.85), 7.5 percent with good fit ($0.84 < R^2 > 0.71$), 15% with moderate fit ($0.70 < R^2 > 0.51$) and 25 percent having either poor or no fit ($R^2 < 0.50$). The information in Column II of Table 12 shows furthermore that: (1) only 52.5 percent (instead of 80 percent in the minimum stress model) of the observers weighted the "tone" dimension predominantly in judging differences in image pairs; (2) the texture information defined by the average 1st and 2nd neighbor contrast statistics of the images was fairly heavily employed by 35 percent of the observers, and (3) finally 12.5 percent of the subjects utilized neither of these statistically defined feature dimensions of "tone" and "texture" in their dissimilarity judgments of these image patterns. This individual differences pattern is also shown in Figure 15. Unlike the result in Experiment 5, the machine solution here shows a perfect fit into this fixed model with an R^2 of 0.993. This is also understandable because this model is fixed according to the computed tone and texture variables of the feature extractor. The weighting factors show the machine solution weighted heavier on the tone dimension than the texture dimension by a factor of 1.5.

E. CONCLUSIONS AND FURTHER CONSIDERATIONS

In our work on digital image processing, we have determined that the essential information for discriminating terrain patterns is contained in 3 to 5 tone-texture variables characterized by the mean density, neighbor contrasts

FIGURE 15: Individual Difference With Respect to the Fixed Model (Terrain Patterns)

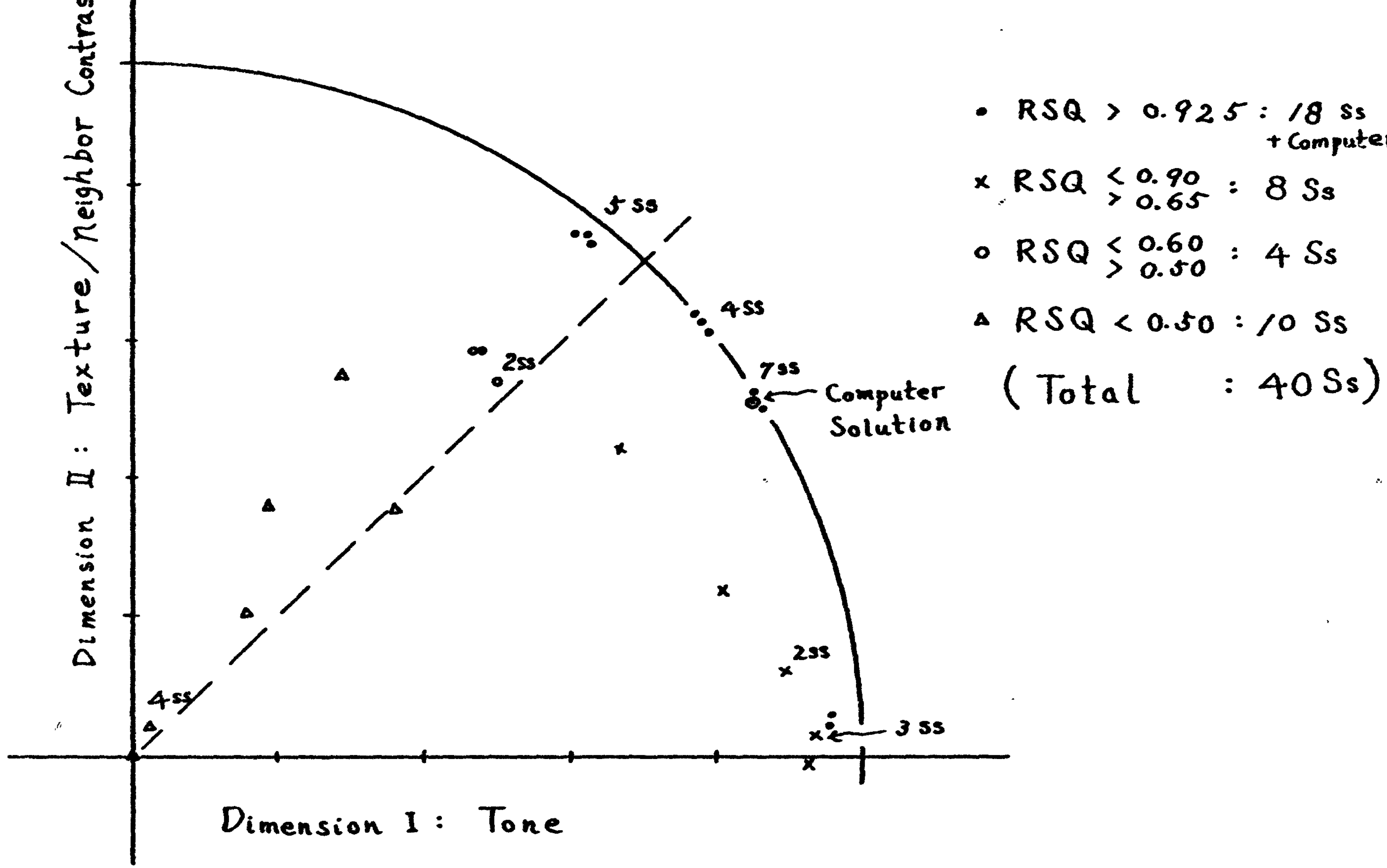


TABLE 11. Individual Differences (Goodness-of-Fit) in Relation to Two Models of Stimulus Dimensions

	Column I: Model Determined With a Minimum Stress Criterion					Column II: Model Fixed With Computered Tone and Texture Parameters				
	R^2	Classification Code				R^2	Classification Code			
1.	0.07				IV	0.30				IV
2.	0.57			III		0.925	I			
3.	0.72		II			0.950	I			
4.	0.73		II			0.002				IV
5.	1.00	I				1.000	I			
6.	1.00	I				0.89	I			
7.	0.99	I				0.65			III	
8.	0.73		II			0.99	I			
9.	0.07				IV	0.93	I			
10.	0.96	I				0.002				IV
11.	0.78		II			0.54			III	
12.	1.00	I				1.000	I			
13.	1.00	I				1.000	I			
14.	0.94	I				0.00				IV
15.	1.00	I				1.000	I			
16.	1.00	I				0.89	I			
17.	0.08				IV	0.38				IV
18.	0.78		II			0.16				IV
19.	0				IV	0.94	I			
20.	0.03				IV	0.94	I			
21.	0.73		II			0.99	I			
22.	0.78		II			0.56			III	
23.	0.97	I				0.06				IV
24.	0.73		II			0.002				IV
25.	0.90	I				0.65			III	
26.	1.00	I				1.00	I			
27.	0.97	I				0.82		II		
28.	0.73		II			0.99	I			
29.	0.96	I				0.54			III	
30.	0.73		II			0.99	I			
31.	0.57			III		0.86	I			
32.	1.00	I				1.00	I			
33.	0.61			III		0.96	I			
34.	0.79		II			0.72		II		
35.	0.73		II			0.26				IV
36.	0.61			III		0.56			III	
37.	0.73		II			0.99	I			
38.	0.96	I				0.002				IV
39.	1.00	I				0.82		II		
40.	0.81		II			0.92	I			
41.	0.73		II			0.99	I			
		17(42.5%)	14(35%)	4(10%)	5(12.5%)		21(52.5%)	3(7.5%)	6(15%)	10(25%)
		Average 0.74, 0.24					Average 0.62, 0.39			

Classification Code (R^2):
I: > 0.85
II: 0.71 - 0.85
III: 0.51 - 0.70
IV: < 0.50

TABLE 12. The Weighting Patterns Tone Versus Texture Criterion (Terrain Patterns)

	Column I: Determined Minimum Stress Model		Column II: Fixed Model	
	40 Subjects	Computer	40 Subjects	Computer
(1) Tone Oriented	32	1	21	1
(2) Even Tone and Texture/Structure	3		7	
(3) Texture/Structure Oriented	1		7	
(4) Neither Tone nor Texture/Structure	4		5	

and skewness parameters derived from a (3 x 3) moving grid. The details of this work has been reported in Hsu/Klimko (1979) under the sponsorship of U.S. Air Force/Rome Air Development Center, Rome, New York.

While we were doing research for Rome Air Development Center, Whitman Richards conducted texture perception studies for the Air Force Office of Scientific Research and concluded that most uniform textures can be perceptually matched (texture metamers) using 3 to 5 variables (greytone levels or filter channels).

These two analyses indicate that important convergences are emerging from the study of human visual perceptive and machine-oriented image processing methods regarding the quest for discovering the elementary building blocks of image (texture) patterns.

The current project represents a further effort to determine the existence of these 3 to 5 elementary variables for the discrimination of real-world terrain patterns by human observers and automated machine classifier systems.

We have approached this research problem using several methodologies including computer simulations (Section B), perceptual tests and machine solutions of choropleth maps (Section C), and perceptual tests and machine solutions using choropleth representations of real-world terrain image patterns (Section D). The results can be summarized as follows:

1. In terms of machine discriminations using the Mahalanobis D^2 statistics, statistically similar patterns of terrain types can be simulated using three elementary tone-texture variables: mean brightness, 1st neighbor contrast and second neighbor contrast. But differences between image and simulated pairs, of course, are still perceived by human observers--such remaining differences undoubtedly are related to "structural" considerations (see below). We also found that variables are sometimes effective for terrain discrimination, but they are very difficult to simulate with numerical methods.

2. Using choropleth maps created from a common data set by varying the class-interval systems for perceptual tests, we found that a two dimensional "texture-tone perception model" quantifiable on the bases of digitized feature statistics, could enable us to describe to a great extent the aspects of human perceptual process in pattern recognition.

3. Using terrain image patterns, additional perceptual tests and similar methodologies, we found, not surprisingly, further evidence for a "structure" dimension (see above) in addition to the tone and texture dimensions in the human perceptual visual system. We are currently exploring ways to separate and fully quantify this third, structural dimension; however, it should be noted that the same two dimensional ("texture" and "tone") model, the dimensions of which are fully quantifiable on the basis of digitized Hsu feature variables, can adequately account for a sizable proportion of the human perceptual process as reflected in pattern discrimination judgments.

4. Considering the weighting vectors of this two-dimensional ("tone/texture") model, machine solutions were typically found to weight the tone dimension heavier than the texture variable by a factor of about 1.5. In contrast, although 75 percent of our human subjects fit very well into this "tone-texture perception model," individual differences regarding the weighting of the tone versus texture dimensions were strikingly apparent. This latter point, of course, has important implications for predicting actual pattern recognition/discrimination judgments by individuals and this respect to training programs, task specific problems, and the development of effectively interactive man-machine system approaches to dealing with the extraction of meaningful and important information from remotely sensed, digitized "image" data.

F. RESEARCH PERSONNEL

Principal Investigator:	Dr. Shin-yi Hsu
Co-Investigator:	Dr. Richard Burright
Research Associate:	Jane Huang
Advanced Research Assistant:	Timothy Masters

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